Climate Change and the Formation of Risk and Time Preferences
A Study of Rice Farmers in Bangladesh

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Abstract

This paper explores the relationship between adverse climate events and the risk and time preferences of rice farmers in Bangladesh. This project uses data from the two waves of Rice Monitoring Survey that were collected by the International Rice Research Institute with funding from the Bill and Melinda Gates Foundation in 2014 and 2017. The paper employs a maximum likelihood approach discussed by Nguyen (2011) and Liebenehm and Waibel (2015) to jointly estimate time and risk preferences as a function of individual attributes as well as various metrics related to the proneness to and experience of farmers with soil salinity, submergence and drought.

We find limited evidence that a farmer's degree of risk proneness interacted with either changing stress frequency or recent loss due to crop stress affected risk aversion. In one model, we observed that increasing frequency of droughts and increasing drought proneness lead to modest but not economically meaningful increases in risk aversion. Contrary to expectations, we find that increasing incidence submergence, drought, or salinity corresponded with declining degrees of risk aversion. We have modest evidence that recent crop losses due to a submergence increase risk aversion, but recent crop losses due to drought yields had a statistically and economically significant effect, with a major loss in the previous year due to drought yielding a large increase in the level of risk aversion.

Increasing drought proneness interacted with increased crop losses had a statistically significant effect on individual time preference parameters and yielded a non-linear relationship with crop losses and patience such that individuals become increasingly patient as losses increase up to a certain point but where more significant losses cause patience to fall again. Finally, increasing incidences of submergence, drought, and salinity have a statistically significant effect; however, the effect is highly nonlinear for submergence and drought such that individuals experiencing either no change or one fewer incidence were the least patient. Also, those reporting substantially fewer cases of salinity demonstrated lower patience than those who reported more frequent incidences of salinity.

Due to the preliminary nature of findings, we defer drawing policy conclusions, but findings provide further evidence of the relevance of weather and climate related events in the economic preferences of farmers.

JEL: D9, D81, Q12, Q54
keywords: climate change, risk preferences, time preference, rice farmers

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Some events such as extreme heat, prolonged droughts, and higher than normal precipitation can be attributed to climate change (National Academy of Sciences, 2016), and rising oceans will certainly cause increasing salinity in coastal areas and estuaries. Adaptations of farmer planting patterns/timing, fertilizer choices, and crop choices that could offset such changes in net farm income would be required. (Thomas et al., 2013), but research suggests that the events in and of themselves could lead farmers to adjust their risk and time preferences and behaviors and thus could change the speed of adaptation. Hurley (2010) identifies research into risk preferences as a key part of understanding farmer responses to risk. To form expectations on such responses, this paper estimates how changes in crop stressors (drought, submergence, and salinity) affect the risk and time preferences of rice farmers in Bangladesh. This project is the first to examine the dynamic effects of climatic events associated with agriculture on both risk and time preferences of farmers.

Given the findings of previous theoretical and empirical research, we arrive at a number of hypotheses about how climate-related stresses may affect farmer time and risk preferences. We hypothesize that, when faced with increases in stressors, individuals from less stress-prone areas and with lower wealth, will demonstrate stronger changes to risk and time preferences than individuals from more stress prone areas and higher wealth. We contend that moderate changes in reported crop stresses will correspond with increased risk aversion among farmers, but due to competing forces, large changes in stressors will have ambiguous effects on preferences. The reference point literature suggests that individuals who report experiencing worse than normal outcomes in the immediately preceding year experience increases in risk aversion and decreases in patience.

In the remainder of this paper, we will first provide something of the context of agricultural production and risk in Bangladesh. Given that introduction, we consider how both the empirical and theoretical literature inform an analysis of how events such as droughts, floods, and soil salinity may affect the patience and risk preferences of farmers. The paper then explains in greater detail the empirical questions, the survey, and econometric approaches. Finally, we explore the statistical and economic significance of our findings.

The Context of Bangladesh

Rice farming and rice related employment continue to represent an important part of agricultural income in Bangladesh, and it continues to provide a vital source of calories for the whole population at over 60% on average per person. (Hossain, 2012) Research indicates that over 90% of farmers plant rice in at least one season, with 27% planting in both Aman and Boro planting seasons. In other seasons, farmers also engage in production of variety of other crops, but rice remains the central element of their farm income and consumption portfolio (Nassim et al., 2017). At the same time and even not accounting for climate change, the risks faced by Bangladeshi farmers are as diverse as the geography of the country. As explained by Nasim et al. (2017), in the high and medium uplands, water scarcity is common, and the vast lowland areas are more prone to flood. In addition, the nutrient rich *haor* in northwestern Bangladesh are especially subject to flooding in the monsoon season but are important productive areas in dry seasons. Nasim et al. (2017) describe three major types of agricultural ecosystems in this diverse system. In irrigated ecosystems, flooding is common, and both droughts and floods can occur in a single season; while in deep water ecosystems waters reach a depth of up to 3 meters for part of the year, and farmers are dependent on the beginning and ending of seasonal floods to time planting and harvesting, and even in that brief window, shallow flooding may continue to occur. Both freshwater and saltwater tidal regions exist closer to the coasts, and both are subject to droughts and floods, while saltwater tidal areas also have the possibility of salinity in soils (either through flooding or through saltwater infiltration into wells). During the monsoon season, rains can dilute salinity and thus make rice growing possible during that one season of the year.

As a consequence of these varied conditions, farmers have adapted their planting patterns. In the dry Boro season, rice is regularly planted in irrigated areas, while transplanted Aman rice is grown in the rainfed lowlands and tidal wetlands during the monsoon period. Traditionally, Aus rice had been planted in the period between the wet and dry seasons in the rainfed uplands, but such planting has fallen as dry season Boro rice has increased in use and fallow or other alternative crops are planted in the traditional Aus season. Finally, a small share of rice is grown in the deep water rice ecosystem via broadcast methods as B. Aman rice. (Nassim et al., 2017).

Given that background, one begins to understand the varied risks. Some farmers anticipate floods or droughts and are now in an environment of increased flooding or droughts due to climate change; while other farmers anticipate salinity but may now be faced with increasing salinity due to ocean rise. In forecasting these changes, Islam (2019) predicts over the next decades that there will be a decline in irrigation needed during the Boro season but that this effect will not be uniform, with increased needs in the southwest and decreased needs in central and northwestern regions. In addition, coastal regions will experience significant increased salinization of up to a 39% increase in soil salinity and a loss of 30% of cultivable land in Chittagong, Dhaka, and Khulna. (Dasgupta et al., 2015) In terms of measured impacts on technical efficiency and output, Mottaleb et al. (2015) find that drought and submergence substantially reduce yields in Bangladesh during the Aman and Aus seasons, with the effects on output on a per family basis being substantially larger during the Aman season. Another important point on agricultural production that these authors make clear is that the Aman season represents a riskier season for farmers in terms of net farm income because rice planted during that season tends to be more dependent on inputs and higher yielding varieties. Consequently, losses during the Aman season are felt more acutely. Ali et al. (2014) also identify an ancillary result from the drought and the flooding. Specifically, they note that the brown plant hopper, a common rice plant pest, appears to perform better as temperatures become hotter and wetter or colder and dryer. If climate change leads to hotter and more humid climates (as suggested in Islam et al. (2019)), then Ali et al.'s findings suggest a threat and risk that is currently unforeseen but represents another challenge which Bangladeshi farmers will confront. In terms of the saline prone areas, Dasgupta et al. (2018) consider the effects of salinity on Boro season rice in Barisal, Chittagong, Dhaka, and Khulna. They find that *upazilla*[2] (thanas) which experience soil salinities greater than 4.0 dS/m (based on electrical conductivity) will experience 15.6% declines in yields. As of 2012, only 18 of these *upazilla* had reached that level, but by 2050, the number would reach 27. Given the above information we learn that farmers in Bangladesh experience different types of risks, with some being subject to regular floods and droughts, some experiencing increased salinization of soils, and many experiencing all three. As one considers the risk preferences and time preferences of farmers, therefore, one must consider appropriate models that reflect (1) the changing or increasing intensity of various threats, (2) the historical patterns of such threats, and (3) the predictability of such threats.

[2] The *upazilla* is the second lowest administrative division of Bangladesh, and there are 492 such administrative units.

Events, Life, and Preference Formation

Risk is an endemic feature of agricultural activity, and farmer's must exhibit intra-seasonal, intra-year, and inter-year patience in their planning on a regular basis. Changing climactic conditions have increased the stresses on farmers activities, and as a result, a wide variety of organizations have invested efforts in developing technologies and whole menus of practices to assist farmer's in their adaptation to such stresses. Holden and Quiggin (2017), Yamano et al. (2018), Liverpool-Tasie, Sanou. and Tambo (2018), and Tran et al. (2019) examine factors that shape farmer adoption of such practices, and importantly, Haile, Nillesen, and Tirivayi (2019) has provide some preliminary evidence that the adoption of a weather-index based crop insurance could actually lead to reductions in risk aversion in other domains. However, to the authors knowledge, no paper has explored the channels for how climate events might change preferences and thus affect future actions.

However, the literature that explores how exogenous factors and endogenous elements can shape both risk and time preferences has grown rapidly in the last decade. Specifically, several authors have developed models to explain how exogenous events affect risk and/or time preferences or consider the endogenous formation of the same, including Gollier and Pratt (1996), Becker and Mulligan (1997), Palacios-Huerta & Santos (2004), Quang (2011), Kettlewell (2018), and Laajaj (2017). Gollier and Pratt examine how unfair background risk can lead to behaviors consistent with increased risk aversion. Palacios-Huerta & Santos (2004) demonstrate how incomplete markets could lead to behaviors corresponding with greater risk aversion among asset poor individuals. Specifically, they argue that incomplete credit markets, for example, could lead asset poor individuals to exhibit more risk averse behavior due to lower access to credit that would otherwise allow individuals to better endure negative events. In the context of life events, Kettlewell (2018) suggests that preference changes may arise from the effects of life events on changes in consumption, changes in the parameters of the utility function under different states, and changes in an agent's emotions. However, Kettlewell does not derive predictions of the directions of change and leaves that to empirical examination.

In terms of time preferences, Becker and Mulligan (1997) model how factors such as wealth, expected mortality, and uncertainty can shape time preferences (or more correctly, the willingness to invest in lowering one's discount rate). Considering only time preferences, Lajaaj (2017) explores how time horizon (discussed as the β in the quasi-hyperbolic discount) function should fall as an individual's prospects and experiences deteriorate. He argues that this arises from an effort to reduce anxiety associated with cognitive dissonance, whereby the dissonance arises from the expected deviation between a person's expected resources in the future relative to some benchmark level of performance. His empirical evidence provides some support for this position. Considering both time and risk preferences, Quang (2011) extends the reference-dependent model of risk preferences elaborated by Koszegi and Rabin (2007) to suggest how past choices shape current time and risk preferences through the medium of changing reference points for risk and time. As with Palacios-Huerta & Santos (2004), he tests this hypothesis and finds evidence that suggests individuals' preferences do change as a result of career experiences. While considered in more detail subsequently, the current project suggests various mechanisms by which experience with changing production risk may affect individuals' measured risk and time preferences. The foundation above suggests that background risk, wealth/income, uncertainty of the future, state-dependent preferences, emotions, reference-dependent preferences, and incomplete markets all could shape preferences.

Empirical efforts to examine how events, experiences, markets, and how individual's choices shape risk or time preferences have grown relatively quickly. Several studies explore how natural disasters (earthquakes, floods, and hurricanes) affect risk preferences in developed country settings (Hanaoka, Shigeoka, and Watanbe, 2018, Kashay and Oberghaus, 2018, Eckel, Gambal, and Wilson, 2009, and Page, Savage, and Torgler, 2014) and each arrives at some evidence of increased risk loving behavior among all or some subset of the population in the aftermath of disasters. Their results are not fully uniform as length of time since a disaster seems to attenuate or even reverse itself in Eckel, Gambal, and Wilson's work (2009). In developing countries, Callen (2015), Cameron and Shah (2015), Cassar, Healy, and Von Kessler (2017), and Chantarat et al. (2019) consider major disasters and their impacts on risk and/or time preferences. Cameron and Shah (2015), Cassar et al. (2017), and Chantarat et al. (2019) find increasing risk aversion in this context; while Callen (2015) finds increased patience, and Chanterat et al. (2019) find decreased patience in response to catastrophes. While climate related catastrophes are likely to increase in frequency (National Academy of Sciences, 2016), climate change also increases "normal" risks (droughts, submergence, and salinity) and requires more planning and investment to mitigate expected challenges.

Another strand of literature considers how violence may affect individual levels of risk aversion. In this regard, care must be taken in considering increased background risk versus background risk. Voors et al. (2012) examine risk and time preferences among Burundians who survived the near total collapse of state with retribution against whole villages – a uniform catastrophe wiping out large parts of whole villages. They find that individuals become more risk preferring and less patient. Brown, Montalva, Thomas, and Velazquez (2019) as well as Callen, Isaqzadeh, Long, and Sprenger (2014) explore how violence affects risk preferences and find that such increases in the general level of risk (due to violence in an area) increases the level of risk aversion or increased desire for certainty among members of a community. In these authors contexts, Mexico and Afghanistan, violence due to drug trade or war was severe to be sure but not as broad reaching. Consequently, for individuals who have experienced a "flood" of unavoidable risk, the research suggests increased risk-taking; however, for individuals experiencing increased overall risk with bouts of increased risk, increased risk aversion appears more common, consistent with Gollier and Pratt (1996). While not as acute as a constant fear of violence, climate change represents an increase in background risk and could therefore shape preferences or expectations.

Exploring Mechanisms of Changing Preferences

The theoretical and empirical literature provide ample foundation for predictions about how climate-related events may affect both risk and time preferences. The following leverages those observations to arrive at channels through which risk preferences and time preferences evolve in response to such events.

Risk Preferences

Some aspects of rice farming in different areas have historical and predictable risks. That is, some areas are drought prone, others are prone to floods, others are prone to both in a given season, and some are prone to salinization. It is entirely possible that some are prone to all three through the seasons of the year. Consequently, where people are located relative to certain risks should be embedded in their preferences for risk. That is, they have already anticipated and/or they have increased experience with such risks, and in the context of that risk, they have taken steps to mitigate the risk or planned accordingly; therefore, while risk preferences may differ across regions, flooding, salinization, or drought consistent with past trends should have limited impact on risk aversion.

It is well established that consumption/income is linked to risk preferences. Specifically, one common element to consider at any time, but particularly at moments of survey, is how and whether a recent sequence of events may have affected an individual's wealth or consumption. While relative risk aversion should remain unchanged over time, the behavior elicited from individuals may exhibit greater risk aversion in terms of the measured coefficients. At the same time, however, climate change, for many farmers in Bangladesh, could be characterized as unfair background risk in that it is mean negative risk added to the existing risky environment. Gollier and Pratt (1996) suggest that additions of such unfair background risk will cause risk averse individuals to behavior more risk averse manners. This change in risk environment is predicted, but unfair, and could imply more risk averse behavior.

Some aspects of risk faced by farmers are unpredicted or deviate from past reported patterns. Given that, when individuals experience changes in flooding, drought, or salinity that deviates from their expected pattern of such events, the effect could be of two types: large events or small events. If a set of weather-related events has a large and negative household income or wealth effect, the decline in wealth could manifest itself in increased risk aversion, with an important caveat. The literature also suggests that individuals experiencing large losses may actually then behave in a risk-preferring manner, although the empirical findings are not uniform in the literature discussed above or in other settings (Suhonen and Saastamoinen, 2018). Specifically, one might argue that if an outcome is negative relative to a person's reference level of income/wealth, then future events will evince less risk aversion or more risk preferring behavior. Such a perspective would be consistent with the theory as laid out in prospect theory; however, if the losses are significant and co-vary with the rest of a person's community, it is possible then that credit markets could be affected; therefore, liquidity constraints might lead an individual to behave in a manner that is more risk averse. That is, regardless of internal desire to perhaps take a bigger bet, one's immediate constraints leads to more risk aversion. Given this ambiguity, we do not have a strong capacity to make a prediction about the direction of risk preferences for large changes without considering specific context. However, if the events or changes are small or moderate, the wealth effect is modest and thus the theory suggests a modest increase in risk aversion. While some authors consider mood/emotional response to negative outcomes, we do not consider that here given the other clear behavioral and economic factors that are likely to shape risk preferences. Given the above, we propose the following hypotheses as to the relationship between negative events such as drought, crop submergence, or worsening soil salinity.

RH.1. Reported increases in drought, submergence, and salinity will affect preferences differently depending on whether a person lives in an area prone to such risks whereby the effects, if any, are more muted for such persons.

RH.2. Moderate changes in reported crop stresses will correspond with moderate amounts of increased risk aversion.

RH.3. Large changes in reported crop stress, will have an ambiguous effect.

RH.4. Conditional on the above, individuals experiencing worse than normal outcomes in the immediately preceding season will demonstrate the largest changes in preferences.

Time Preferences

As discussed in the literature, time preferences are considered as being linked to risk preferences (Anderson et. al (2008), Nguyen (2011), and Liebenehm and Waiebel (2015)); however, there is ample literature as discussed above which explores how time preferences alone may be affected by economic or personal events. As above, if negative events shape wealth, then, according to Becker and Mulligan (1997), such individuals would unambiguously have higher discount rates on the future relative to individuals who did not experience such stresses. As suggested in Nguyen (2011), if an individual must choose to exercise patience as a consequence of some event or events, then that could lead their level of patience to increase. That is, if the events create opportunities to exercise patience, then those individual's patience levels would be higher than those who had less such experience, controlling for other factors. Again, individuals living in more stress prone areas will have experienced more economic stress in the past and therefore will have greater patience all other things held equal. At the same time, Becker and Mulligan (1997) argue that expectations of the future can change an individual's demonstrated level of patience. That is, the effects of climate change on expectations may manifest itself in differential levels of patience. Some of this may depend on the person's sense of agency or ability to respond effectively to risks in the future. For example, if a farmer perceives the future challenges of the climate as manageable and requiring only reasonable levels of additional investment in the short to medium term, then their general level of patience may be unchanged or even higher because of the salience of future events given recent experiences. However, for those farmers with less experience or living in less prone areas, additional stresses in farming could undermine their ability to consider the future due to current stresses. In a worst-case scenario, for both types of farmers, recent production experiences could well foreclose a reasonable anticipation of their future in the current area or the deviation between some reasonable threshold and what the person perceives as possible may shorten a person's time horizon as suggested by Laajaj (2017). Such behaviors may arise from some sense of cognitive dissonance (Laajaj, 2017), or it may simple be a rational response to legitimately limited future capacities for success in farming (Becker and Mulligan (1997)). As suggested in the literature, from the farming perspective, it is entirely possible that some areas will become unmanageable to farm as a result of changing climates; therefore, those that survive in such areas would necessarily have made a wholesale change in income generation, and one might reasonably argue that such individuals are rather more exceptional individuals than typical. Given the above, following are our general hypotheses about the relationship between stressors and time preferences.

TH.1. All things else held equal, the effect of stresses (drought, flood, salinity) will be stronger for individuals in areas less traditionally prone to such stresses.

TH.2. Income/Wealth effects associated with changes (loss in crop production) in stresses will cause patience to fall, with impacts being greater for larger stresses.

TH.3. Perceptions of greater stresses in the future will tend to correspond with individuals raising their level of discount on the future.

Data and Methods

Data Sources and Construction

This paper uses Rice Monitoring Survey data collected by the International Rice Research Institute with funds from the Bill and Melinda Gates Foundation (RMS, 2019). The panel of data includes 1,485 households collected in 2014 and 2017 from 16 districts in six divisions of Bangladesh. In addition to demographic, economic, self-reports of recent and historical crop stressors, and related household data, data includes information on risk and time preferences. Risk preferences were elicited using a gamble choice game based on Binswanger (1980) and closely related to other studies (Barr and Genicot 2008; Cardenas and Carpenter 2008; Cameron and Shah 2010; Eckel and Grossman 2002, 2006). Time preferences were elicited using a multiple price list survey consistent with Collier and Williams (1999). At this stage of the study, data from Dasgupta, Hossain, and Wheeler (2015) was used to match individuals to expected proneness to salinity stress, and survey information on the proportion of land which households farm that is characterized as high land and low land measures the proneness of fields to dryness or submergence, respectively. However, additional daily data on precipitation and temperature are being gathered in order to construct metrics of season, monthly, and annual measures of temperature and precipitation averages, variation, and totals, as appropriate (e.g., a standardized precipitation index). While still in process, these will be developed around the various methods discussed in Rahman et al. (2017), Mottaleb et al. (2015), Arslan et al. (2017), and Asfaw et al. (2014). Beyond these measures, the current paper will consider three different measures of either current stress associated with submergence, drought, and salinity. First, the rice monitoring survey asked respondents whether they perceived submergence, drought, and salinity as crop stressors. Second, in each year of the study, individuals were asked in how many of the previous five years did they experience the particular stressor (i.e., 0 to 5 years). Because we are interested in how changes in this value or stressor affect preferences, we take the difference between the households reported 5-year experience in 2016 from the reported 5-year experience in 2014. In this way, we are able to measure the extent to which decreasing or increasing intensity of a stressor affects individual preferences. Finally, individuals were asked whether they experienced submergence, drought, or salinity in the current crop year and the percentage crop was lost due to that stressor. Because the economic effect of the stressor is that which we believe will shape and or affect the household preferences, we calculated the implied crop loss as a percent of what the farm would have produced had they not experienced the crop stressor. Details are discussed in Appendix 3, but the general idea is to provide a measure of the deviation of output from expected output assuming average local production conditions at the village level.

In addition, to control for wealth and changes in economic condition, various metrics were calculated. The primary sources of wealth, aside from rice stocks, are land, physical assets other than residence, and animal assets. The survey instrument did not include a specific question about home attributes, so we cannot directly consider this piece of information in this analysis. Two approaches were used in order to construct measures of wealth: (1) using available price/value data to construct values for land, physical assets, and animal assets based on some base year values and (2) pursuing the principal components index value construction proposed by Filmer and Pritchett (2001). There are merits to considering both approaches; therefore, we consider estimations using both. Details on this construction appear in Appendix 1. In order to capture both current wealth and changing conditions, the study incorporates metrics of the respondents' current wealth and their change in wealth from the previous period. Because findings from the method (1) measurement and method (2) measurement are largely similar, we only report information on the first metric here.

Summary of Key Elements of Data

Table 1 provides the general traits of the sample. Note, while the original panel of data was ostensibly 1485 households, this data set was reduced by the following conditions. First, because we are incorporating the experimental findings that include two periods of self-reported data on assets and output, we only include households where the respondent was constant over time. At this time, we include 865 observations of the panel due to data availability across both periods, and we are reviewing some observations in the full data set for consistency before incorporating them. With that preliminary information, we note that about 94% of the sampled group were male and had an average age of 49 at the time of the 2017 survey and had received six years of education. Approximately 15% of the sample was Hindu, and the average family size was close to 6 individuals. An observable trait that might strongly correlate with an individual's risk preferences is the extent to which the household head participates in leadership activities in the community, and we note that most household heads did not lead community or related organizations. Two areas which might signal a household's capacity to mitigate risk include irrigation and distance from output markets. Finally, we want to control for changes in household wealth and current wealth. We note that average reported change in wealth was quite high. Given that constant prices were used, the data suggest significant increases in wealth within this sample set. In addition, we note a wide variability in household wealth in terms of taka.

In the context of this data, we find that the mean salinity in the data is slight but that the communities within the data set range from very high salinity to no salinity. In terms of land shares in high land versus low land, nearly 50% of land holdings were on low land and thus are considered more likely prone to flooding, and about 15% of farmer's lands were on high land, thus being more prone, on average, to drought. In terms of actual loss to stresses, mean crop losses range from about 8%, 1%, and 0.5% of crop production due to submergence, drought, and salinity, respectively. Note, however, extreme losses occurred under all categories, ranging from a loss of 47% of crops as a maximum due to drought up to 95% of crops due to submergence. These results correlate with what farmers state as the changing frequency of these stressors and their overall assessment of these stressors as problems in rice production.

Table 1. Summary Statistics of Variables Used in Analysis

Household and Farm Characteristics	#obs	Mean	Std. Dev.	Min	Max
Sex	865	0.06	0.23	0	1
Age	865	49.08	12.15	20	84
Education	865	6.03	4.32	0	17
Hindu	865	0.15	0.36	0	1
Family Size	865	5.67	2.54	2	23
Household Head Leadership	865	0.24	0.58	0	4
Distance from Output Market	865	2.07	1.88	0	12
Irrigation	862	0.71	0.45	0	1
% Change in Non_Land Wealth (in Taka)	833	270.66	2034.49	-100	38738.81
Total Wealth (Taka)	864	788956.8	352892.4	0	2220137
Salinity Index (0 No Salinity to 7 Very High Salinity)	865	0.95	1.66	0	7
% of Land on High Ground	864	0.15	0.26	0	1
% of Land on Low Ground	864	0.47	0.42	0	1
Loss and Stress Measures					
Share of Crop Lost Due to:					
Submergence	861	0.08	0.16	0	0.95
Drought	861	0.01	0.03	0	0.469565
Salinity	861	0.01	0.03	0	0.7
Change in Reported Frequency (2013-2016)					
Submergence	865	0.93	1.93	-5	5
Drought	865	0.62	2.38	-5	5
Salinity	865	0.30	1.49	-5	5
Opinion on Stressor as Problem (1 = Strongly disagree that stressor is a problem and 5 = Strongly agree that stressor is a problem)					
Submergence	865	3.52	1.30	1	5
Drought	865	3.04	1.27	1	5
Salinity	865	2.22	1.20	1	5

Before moving on to the empirical model, a slightly more nuanced discussion of the changes in reported stressor frequency as well as general opinion of a stressor as a problem is merited. Figure 1 on the following page shows how individuals reported changes in stressors between the 2014 and 2017survey. Note, each survey asked individuals how often they had experienced submergence, drought, and salinity in the previous five years at the time of the survey. In the case of drought and submergence, a large number of participants reported no change in their underlying conditions. Therefore, if they reported experiencing submergence three of the previous five years in the 2014 survey and again experience submergence in three of the previous five years in 2017 survey, they would show no change in their submergence experience. Note, this value is important as it reflects the fact that farmers should respond to changes in experiences in addition to the experience itself. At the same time, for both drought and salinity, important densities of participants appear to perceive increasing frequency of droughts and submergence. Salinity is more geographically confined in the sample, and while Dasgupta et al. (2018) suggest that the conditions will worsen over the next decades, it is less likely that large changes in salinity would be perceived in the short period between the two rounds of this survey. Nonetheless, it appears that some households are experiencing greater degrees of salinity. Objective data that matched households to salinity indices according to Dasgupta et al. (2018) reveals the proportions of households fitting into different degrees of salinity is shown in Table 2, revealing about 15% of the sample lived in areas with moderate to extreme salinity.

Figure 1. Changes in Stressor Experiences

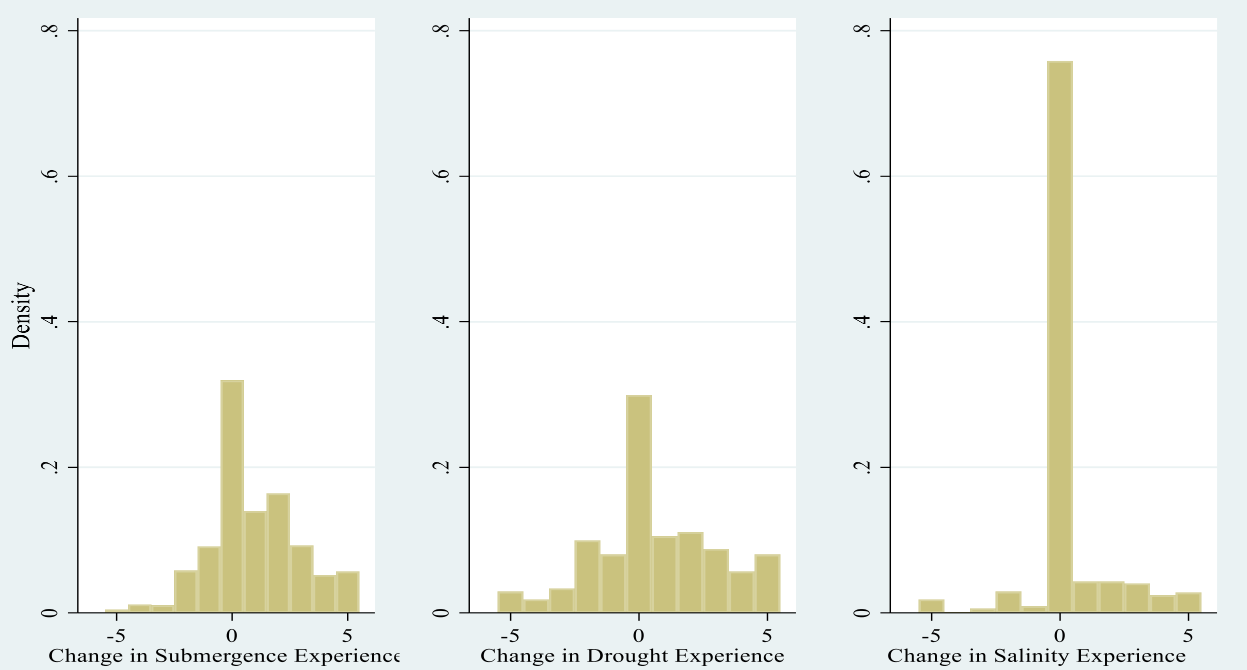


Table 2. Distribution of Households by Salinity Index

	Frequency	Percentage
Non-saline	543	62.77
Slight salinity	127	14.68
Slight to moderate salinity	57	6.59
Moderate salinity	70	8.09
Moderate to High Salinity	25	2.89
High Salinity	13	1.5
Extreme Salinity	30	3.47
Total	865	100

With that information, our sample contains a diverse population of individuals based on regions, assets, observable household traits, stress proneness, opinions on stress, observations of changes in stress, and measured impacts of stress on output suggesting ample variation to identify how various stress affect both time and risk preferences.

Empirical Approach

In order to estimate the relationship between observable traits, wealth, and stressors and the households risk and time preferences, this paper will further employ the approach articulated by Liebenehm and Waibel (2015) and Nguyen (2011) to estimate the effects of changes on climactic stress on risk and time preferences. This method recognizes Andersen et al's (2008) argument that estimating time preferences separately from risk preferences may affect the estimates of individuals measured time preference. First, assume that x is some immediate payment and y is some payment to be received in the future and where D represents some function of the vector of discount parameters Γ and the delay in time is t. It has been argued that when one finds the discount function by solving the following equation: $x = D(\Gamma, t)*y$ that one is assuming that individuals are not considering potential risk of receiving some reward by some future date. Consequently, both Nguyen (2011) and Liebenehm and Waibel (2015) propose that it may be appropriate hto think of deriving the estimates such that $U(x) = D(\Gamma, t)*U(y)$ so that, if a person's risk preferences are embedded in their utility function, then one can gain a more appropriate measure of individual discounts on money.

The following discussion adheres to the methodological explanations provided by Liebenehm and Waibel (2015) and Nguyen (2011). Before explaining this model in greater detail, we make a brief aside on the empirical approach taken here. In our experimental elicitation procedure, there were two activities where individuals were asked their preferences of risk opportunities and about their level of willingness to delay risks. In the risk preference elicitation, individuals were asked which prospect among five possible prospects they preferred. These options were ordered in terms of riskiness, ranging from a certain reward to increasingly risky opportunities. While Liebenehm and Waibel (2015) and Nguyen (2011) presented a larger number of purely binary options to respondents, they enforced monotonic switching in the decision process. For example, in their first risk elicitation activity these authors presented individuals with 14 pairs of options A and B where option A remained constant over the range of pairs and option B became increasingly risky. Individuals were permitted to choose all A, all B, or switch from A to B at a single time. This sequence choices became a binary variable in their econometric method. Consequently, as we apply this econometric method, we will treat the five options as if they were a series of four comparisons between A and B so that if a person preferred the certain option to the next less certain option, then transitivity would imply that they preferred that option to all others as well. For the time preference elicitation in this survey, individuals were given the opportunity of choosing between a delayed reward with a delay of one year or an immediate reward. While much less variability in delay and reward values occurred as a result of the original survey design, this elicitation process more closely aligns with those used in Liebenehm and Waibel (2015), thus no modifications are required in this element of the study.

In any case, we can now move forward with an explanation of the empirical approach taken. If the individual chooses A, they receive an instantaneous utility of U(A), and if the person chooses to receive B, they receive an instantaneous utility of U(B) and the discounted utility of D(Γ, t)*U(B). For estimation purposes, as explained by Nguyen (2011), we must assume a particular utility function as part of the random utility function approach to estimation. Let us assume that V is the assumed utility function and that D is the assumed discount function, and in the final estimation, the extent of errors will be greater or lesser depending on the proximity of the assumed function to the individual's true function. In this project, V is assumed to follow a simple utility function that aligns well with multiple models of utility (i.e., $V(x) = x^{\alpha}$). Let Z_i be the economic and demographic characteristics of individual i. As will be explained further later, the exponential model with a fixed cost present bias is assumed for the D function. In addition, denote U_i^{Aj} and U_i^{Bj} as the utilities that individual i receives when faced with choice j. In theory, for any given sequence of selections, it is assumed that error terms ε_i^{Aj} and $\varepsilon_i^{Bj}$are identically and independently distributed across individuals such that $\{\varepsilon_1^{Aj}, \varepsilon_2^{Aj}, \varepsilon_3^{Aj}, \ldots, \varepsilon_N^{Aj}\}$ are independently and identically distributed (i.i.d.) and follow a normal distribution, and $\{\varepsilon_1^{Bj}, \varepsilon_2^{Bj}, \varepsilon_3^{Bj}, \ldots, \varepsilon_N^{Bj}\}$ are independently and identically (i.i.d.) and follow a normal distribution.

For the risk experiments, we can summarize the relevant utilities as follows:

$$U_i^{Aj} = V_i^j\big((A_j, p); Z_i\big) + \varepsilon_i^{Aj} \quad (13)$$

$$U_i^{Bj} = V_i^j\big(B_j, (1-p); Z_i\big) + \varepsilon_i^{Bj} \quad (14)$$

For the time experiments, we can summarize the relevant utilities as follows:

$$U_i^{Aj} = V_i^j\big(A_j; Z_i\big) + \varepsilon_i^{Aj} \quad (15)$$

$$U_i^{Bj} = D_i(\Gamma; t; Z_i)V_i^j(B; t; Z_i) + \varepsilon_i^{Bj} \quad (16)$$

Given the distribution of error terms, let the joint density of the distribution of errors across individuals be written as follows f(ε). As explained in Nguyen (2011), we can derive the likelihood function as follows for the case of intertemporal choice, but this approach applies with very slight notational modifications to the choices under uncertainty as well. First, let the probability that the agent chooses option A be the following.

$$\Pr(A) = \Pr\,(U_i^{Aj} - U_i^{Bj} \geq 0)$$

$$= Pr\big\{V_i^j\big(A_j; Z_i\big) + \varepsilon_i^{Aj} - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) - \varepsilon_i^{Bj} \geq 0\big\} \quad (17)$$

This expression can be modified to be restated as follows:

$$\Pr(A) = Pr\big\{V_i^j\big(A_j; Z_i\big) - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) \geq \varepsilon_i^{Bj} - \varepsilon_i^{Aj}\big\} \quad (18)$$

As a result, the probability that the person chooses A can be determined by the cumulative distribution of the error term $\Phi(x) = \int_x f(\varepsilon)d\,\varepsilon$ and can be stated as follows

$$\Pr(A) = Pr\big(V_i^j\big(A_j; Z_i\big) - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i)\ \big) \quad (19)$$

Following on that, we can define the latent option for A and B in each scenario j as follows.

$$I_i^{Aj} = V_i^j\big(A_j; Z_i\big) - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) \quad (20)$$

$$I_i^{Bj} = D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) - V_i^j\big(A_j; Z_i\big) \quad (21)$$

From this, we can speak of $\Pr(A) = \Phi\left(I_i^{Aj}\right)$ and $\Pr(B) = \Phi\left(I_i^{Bj}\right)$. To apply the maximum log-likelihood estimation technique, we note that the log-likelihood for each individual depends on the utility function parameters (α) under expected utility theory and (δ, κ) under the exponential time discounting function with a fixed cost present bias component. As explained by Liebenehm and Waibel (2015), the utility of each lottery pair in scenario j can be expressed as a latent index $I_i^j(\Delta U) = U_i^{Bj} - U_i^{Aj}$, and this latent index for individual i and choice j is linked to the observed binary choices (or in our case, the constructed binary choice for risk and observed for time) made by survey respondents in the experiments through the standard cumulative distribution function $\Phi(I_i^j)$. In order to permit the statement of the likelihood, assume that Zj corresponds with the relevant choice-based information (i.e., time and payoffs for the time-based choices and probabilities and payoffs for the risk-based choices). Given that statement, we can expression the log likelihood function as follows. If $y_i^j = 1$ then individual i has chosen option A in scenario j and when $y_i^j = 0$ then individual i has chosen option B in scenario j.

$$lnL^i\ \left(\alpha, \kappa; y^j, X_i, Z^j\right) = \sum_{j=1}^{14}\left\{\left[ln\varphi\left(I_i^{Aj}\right)|y_i^j = 1\right] + \left[ln\varphi\left(I_i^{Bj}\right)|y_i^j = 0\right]\right\}$$

For a given agent i, likelihood is maximized over the 14 choices that individuals made during the experimental rounds (four in Activity 1 and ten in Activity 2). The procedure used was a modified version of code developed by Waibel and Liebenehm (2015).

This estimation approach permits various specifications of the utility or value function of the agent, and it permits various discount function specifications. While estimation of the constant relative risk aversion parameter estimation is common in such settings, we assume, as with Nguyen (2011), Liebenehm and Waibel (2015), that the value or utility function takes a much simpler form such that the utility of some value x can be written as $V(x) = x^{\sigma}$, where σ represents the degree of risk aversion of the individual. Our survey approach does not permit a nesting of this within the context of cumulative prospect theory, but we believe the insights will nonetheless reveal important implications. In addition, the estimation method also permits the consideration of multiple discounting models (exponential, quasi-hyperbolic, and a fixed-cost present bias model). We attempt to estimate individual and aggregate discounting behavior under each of those specifications.

Model Variations

In order to implement this estimation method, we consider three basic models and two models which allow for a greater consideration of the hypotheses posed. Table 3 below outlines the various models considered. Notably, other appropriate specifications were also considered, but given the method of estimation, not all models converged.

Table 3. Alternative Models of Stressors and Preferences

Model 1.	Opinion Submergence Opinion Drought Opinion Salinity	Salinity Index (0 No Salinity to 7 Very High Salinity) % of Land on High Ground % of Land on Low Ground
Model 2.	Change Submergence Change Drought Change Salinity	Salinity Index % of Land on High Ground % of Land on Low Ground
Model 3.	Change Submergence Change Drought Change Salinity % Crop Loss Due to Submergence % Crop Loss Due to Drought % Crop Loss Due to Salinity	Salinity Index % of Land on High Ground % of Land on Low Ground
Model 4.	Change Submergence Change Drought Change Salinity	Salinity Index*% Crop Loss Due to Salinity % of Land on High Ground*% Crop Loss Due to Drought % of Land on Low Ground*% Crop Loss Due to Submergence
Model 5.	Change Submergence Change Drought Change Salinity % Crop Loss Due to Submergence % Crop Loss Due to Drought % Crop Loss Due to Salinity Large Loss Dummy Variable	Salinity Index* Change Submergence % of Land on High Ground* Change Drought % of Land on Low Ground* Change Salinity
	Common Variables	
Measures of Ability to Cope with Stress	% Change in Non_Land Wealth (in Taka) Total Wealth (in Taka) Irrigation Distance from Output Market	
Household Characteristics	Sex Age Education Hindu Family Size Household Head Leadership	

In each of our base models (Models 1, 2, and 3) we include the degree of stress proneness of a farmer as measured by the farmer's corresponding salinity index and land shares measured as high and thus more drought prone land and land shares measured low and thus more submergent prone land. Subsequent work will also include proper precipitation and temperature indices to better control for proneness to stresses. Model 1 includes only the respondents' opinions as to whether they believed a particular crop stressor was a problem in their production. While some authors consider the use of self-reported stress as likely to lead to a reverse causality problem (Liebenehm, 2018) in the estimation of risk and time preferences because individuals who claim greater problems with such stressors might, in fact, be more risk averse and thus more attuned to risk, we consider them as reasonable first efforts as part of this larger study and will allow us to compare the relative strength of opinion measures as being statistically and practically related to a households risk and time preferences. Model 2 includes only the extent to which a household reports a change in their flood, drought, and salinity experiences between the two survey periods. Ideally, this would allow us to capture the extent to which farmers are having to adjust to changing cropping conditions due to abiotic stresses over time. It is worth noting that the stress variables in Model 1 and Model 2 are highly, but not perfectly, correlated with one another. For example, the Opinion Submergence variable and the Change Submergence variable have a correlation coefficient of 0.52. It is for this reason that we do not include all six in a single regression as that would impede our ability draw meaningful inference about the relationships. Model 3 includes both the metrics of change in stressors and the farmer's most recent year planting losses due to crop stressors. In this manner, we attempt to measure the extent to which farmer's perception of change in stressors over time affect preferences along with the farmer's most recent year experience with stressors.

Models 4 and 5 are included as attempts to more accurately test our hypotheses as to whether stress proneness before a changing trend of outcomes or before a particularly poor year mitigates changes in risk and time preferences. Model 4 is similar to Model 3; however, instead of allowing the crop share and stress proneness variables to enter separately, we use their interactions. For example, we include the interaction between the salinity index and the % of crop lost in the most recent year due to salinity to capture both how a recent year loss and stress proneness affect risk and time preferences. Finally, Model 5 includes the same non-interacted regressors as Model 3, but it also allows for an interaction between the measures of observed change in stressors with their respective stress proneness variables. This serves a similar purpose as the interaction in Model 4 but allows us to consider how the interaction with a person's perception of the change in stressors relates to risk and time preferences.

Four measures in the regression control for, to some extent, farmer's ability to mitigate risk or a measure of their most recent experience of a change in such ability to cope. Specifically, we control for changes in non-land Wealth from that held in the first round of the survey as well as a measure of the farmer's total current wealth. Note, we recognize that both of these variables are endogenous and have plans to control for that in subsequent iterations of this project, but we omit that correction for the time being as that is not a primary focus on the current project. Similarly, whether a farmer has irrigation can both act as insurance against risk and allows farmers to have a longer cropping time horizon, but it is obviously the case that farmers with greater degrees of risk aversion and more patience might well be more likely to purchase the equipment necessary for irrigation if they are able. We include distance from the nearest output markets to reflect a farmer's ability to mitigate the risk of lost crops due to stressors. That is, if a farmer is closer to an output market, they may have less risk because they have easier access to supplementary supplies, credit, and other resources should they have shortfalls in crops due to a crop stressor. It also likely reflects some possibility for access to alternative income sources. Note, the remaining regressors such as age, gender, education, family size, and observed household head behaviors are common in such methods and act as proper controls on observable differences in individuals.

Empirical Findings

We present our empirical findings at this point. First, we will present our findings related to the baseline estimation of risk and time preferences over the whole population. We then present the findings from our five models. As explained before, we assume a simplified specification on the utility function in a manner consistent with other users of this estimation method that allows us to measure risk preferences (Nguyen, 2011; Liebenehm and Waibel, 2015). We also attempted to estimate the models according to the exponential, quasi-hyperbolic, and fixed-cost present bias model, but we found that the Stata maximum likelihood estimation approach did not yield results for the exponential and quasi-hyperbolic model because it could not calculate numerical derivatives due to discontinuous region with missing values encountered. This is a technical issue that we are reviewing for possible solutions. However, for the purposes of this paper, we obtained estimates for the exponential model that includes a present bias parameter. As explained by Benhabib, Bisin, and Schotter (2010), this model has performed well in experimental settings. Unlike the quasi-hyperbolic model which converges to the exponential model for sufficient time delays, the present bias model assumes that there is fixed difference between a simple exponentially discounted model and a present biased model. So, the baseline model we are effectively estimating without controls for observable characteristics of individuals is as follows where σ represents the risk preference parameter, δ represents the discount rate, and κ is the fixed time bias parameter. The parameter estimates should all take a positive value in theory.

$$U = e^{-\delta t} * x^{\sigma} - \kappa$$

Baseline Results

Table 4 provides the results for each of the parameters of this equation. We note that the results suggest that individuals in this sample are highly risk averse and that their discount δ is very large in that it implies a 189% annualized discount rate, very large, but certainly not inconsistent with some findings in the literature. However, we obtain an unexpected result for κ that offsets the high discount rate on the future for small dollar amounts. This suggests a fixed-bonus discount model for low rewards. On net, these time preference findings suggest that all values regardless of magnitude have an extremely steep discount in the first year, converging to a long-term present value equal to some fixed amount associated with κ and simply highlights the overall extreme present-mindedness of the population from which the sample was drawn.

Table 4. Baseline Findings

	Coef.	Std. Err.	Z	P>z	95% Conf. Interval	
σ	0.2903	0.0326	8.89	0	0.2263	0.3543
δ	1.8994	0.3818	4.97	0	1.1511	2.6477
κ	-2.3628	0.8126	-2.91	0.004	-3.9554	-0.7701
Log pseudolikelihood		-6443.85				
# of Observations		12,110				

We also admit appropriate criticisms of the experimental techniques used in the original survey. A very simple elicitation process was used given the large sample size, time limits in survey execution, and expense that yielded data which perhaps made it more likely that we found such limiting results. Nonetheless, we believe that differentials in the determinants of δ and κ still yield important information on the role which abiotic stress experiences in the discounting behavior of farmers.

Empirical Findings for Individualized Estimates

Table 5 below presents the model statistics for each model used. We use the empirical method proposed above and include Newey-West and Cluster corrections for standard errors, recognizing that that each observation is a household-preference combination. Specifically, each household responded to five risk preference-related questions (which are condensed to the equivalent of four comparisons) and ten time preference-related questions; therefore, with between 830 and 831 households depending on model, total observations ranged from 11,620 and 11,634. Briefly, we can reject the null that the parameters in these regressions are all simultaneously equal to zero.

Table 5. Model Statistics

	Log-pseudolikelihood	Wald χ^2	Prob > χ^2	# of Household clusters	# of obs
Model 1	-5692.95	113.83	0	831	11,634
Model 2	-5763.6122	223.62	0	831	11,634
Model 3	-5749.02	223.62	0	831	11,634
Model 4	-5677.7133	271.49	0	830	11,620
Model 5	-5650.64	416.75	0	830	11,620

In the rest of our discussion of the statistical properties of our parameter estimates, we focus only on the values associated with our stressor and stress proneness variables. We include complete results in Appendix 3 for inspection.

Risk aversion, Stress Proneness, Opinions on Stress, and Stress Experience

We first consider the relationship between opinion of stressors and a farmer's estimated risk preferences. This piece of the project does not fit directly with our proposed hypothesis, but from an exploratory perspective, we might wish to compare those findings with what we find for other objective metrics. We then consider the role of stress proneness and stress proneness interacted with either observed changes in stress experience or in observed losses in crops due to crop stressor. We then consider how farmers' perceptions of changes in the crop stressor, percentage losses due to crop stressors, or extreme losses in a year as a whole relate to farmer risk preferences.

Table 6. Comparisons of Parameters on Stressor Metrics as Determinants of Risk Aversion																				
	Model 1				**Model 2**				**Model 3**				**Model 4**				**Model 5**			
	Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval	
Proneness Measures																				
Salinity Index	-0.008	0.161	-0.020	0.003	-0.022	0.067	-0.046	0.002	-0.004	0.895	-0.065	0.057								
% High Ground	-0.012	0.743	-0.082	0.058	0.071	0.167	-0.030	0.171	-0.005	0.933	-0.111	0.102								
% Low Ground	0.009	0.572	-0.023	0.042	-0.009	0.821	-0.087	0.069	-0.005	0.864	-0.066	0.055								
Frequency Interaction																				
% Low Ground*ΔSubmerg													-0.009	0.495	-0.035	0.017				
% High Ground*ΔDrought													-0.001	0.944	-0.020	0.019				
Salinity Index*ΔSalinity													-0.008	0.000	-0.012	-0.004				
Share Interaction																				
% Low Ground*Interaction																	0.022	0.936	-0.512	0.556
% High Ground Interaction																	-1.081	0.124	-2.460	0.298
Salinity Index Interaction																	-0.035	0.931	-0.830	0.760
Opinion on Stressor																				
Submergence	0.008	0.258	-0.006	0.021																
Drought	-0.029	0.044	-0.057	-0.001																
Salinity	-0.022	0.012	-0.039	-0.005																
Change in Frequency																				
Submergence					-0.006	0.496	-0.023	0.011	0.009	0.062	0.000	0.018	-0.005	0.423	-0.016	0.007	0.009	0.061	0.000	0.019
Drought					0.007	0.076	-0.001	0.015	-0.001	0.770	-0.010	0.008	0.007	0.032	0.001	0.014	-0.002	0.601	-0.009	0.005
Salinity					0.025	0.022	0.004	0.047	0.022	0.008	0.006	0.039	0.038	0.000	0.027	0.049	0.024	0.000	0.013	0.035
Share of Crop Lost Due to:																				
Submergence									-0.168	0.071	-0.350	0.014					-0.020	0.954	-0.693	0.653
Drought									1.379	0.000	0.827	1.930					2.129	0.000	1.468	2.791
Salinity									-0.263	0.855	-3.085	2.560					0.184	0.898	-2.629	2.998
Large Loss Dummy																	-0.091	0.261	-0.250	0.068

Table 7. Comparisons of Parameters on Stressor Metrics as Determinants of Discount Rate

	Model 1				Model 2				Model 3				Model 4				Model 5			
	Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval	
Proneness Measures																				
Salinity Index	-0.112	0.229	-0.295	0.070	-0.274	0.024	-0.513	-0.035	-0.103	0.756	-0.753	0.547								
% High Ground	-0.024	0.955	-0.843	0.795	0.524	0.405	-0.711	1.760	-0.328	0.632	-1.667	1.012								
% Low Ground	-0.105	0.615	-0.512	0.303	-0.254	0.620	-1.257	0.750	-0.263	0.536	-1.095	0.570								
Frequency Interaction																				
% Low Ground*ΔSubmerg													-0.226	0.188	-0.562	0.110				
% High Ground*ΔDrought													-0.264	0.072	-0.552	0.024				
Salinity Index*ΔSalinity													-0.102	0.002	-0.165	-0.038				
Share Interaction																				
Salinity Index Interaction																	-0.678	0.850	-7.704	6.349
% High Ground Interaction																	-15.409	0.037	-29.887	-0.930
% Low Ground*Interaction																	-3.016	0.463	-11.078	5.046
Opinion on Stressor																				
Submergence	0.108	0.152	-0.040	0.255																
Drought	-0.225	0.089	-0.483	0.034																
Salinity	0.005	0.966	-0.215	0.224																
Change in Frequency																				
Submergence					0.220	0.000	0.132	0.307	0.109	0.057	-0.003	0.220	0.056	0.470	-0.095	0.207	0.145	0.016	0.027	0.264
Drought					-0.038	0.688	-0.224	0.148	0.115	0.050	0.000	0.230	0.255	0.000	0.173	0.338	0.102	0.025	0.012	0.191
Salinity					0.268	0.024	0.036	0.499	0.254	0.003	0.084	0.425	0.409	0.000	0.251	0.567	0.273	0.000	0.152	0.393
Share of Crop Lost Due to:																				
Submergence									-2.150	0.031	-4.106	-0.195					1.260	0.775	-7.361	9.880
Drought									12.665	0.000	6.637	18.693					20.866	0.000	13.263	28.470
Salinity									-5.620	0.670	-31.491	20.252					6.348	0.690	-24.852	37.549
Large Loss Dummy																	-1.613	0.106	-3.567	0.340

Table 8. Comparison of Parameter Estimates on Stressor Metrics on Time Bias

	Model 1				**Model 2**				**Model 3**				**Model 4**				**Model 5**			
	Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval		Coef.	P > z	95% Confidence Interval	
Proneness Measures																				
Salinity Index	0.202	0.262	-0.150	0.553	0.622	0.015	0.121	1.123	0.227	0.781	-1.372	1.827								
% High Ground	0.525	0.584	-1.356	2.405	-1.382	0.368	-4.390	1.627	0.821	0.574	-2.045	3.687								
% Low Ground	-0.146	0.761	-1.085	0.794	0.386	0.716	-1.695	2.466	0.413	0.647	-1.354	2.180								
Frequency Interaction																				
% Low Ground*ΔSubmerg													0.292	0.407	-0.397	0.981				
% High Ground*ΔDrought													0.364	0.257	-0.265	0.993				
Salinity Index*ΔSalinity													0.273	0.004	0.085	0.460				
Share Interaction																				
Salinity Index Interaction																	0.549	0.942	-14.257	15.355
% High Ground Interaction																	36.888	0.092	-6.014	79.791
% Low Ground*Interaction																	9.086	0.385	-11.393	29.566
Opinion on Stressor as Problem																				
Submergence	-0.178	0.376	-0.570	0.215																
Drought	0.655	0.025	0.084	1.227																
Salinity	0.044	0.851	-0.417	0.505																
Change in Reported Frequency																				
Submergence					-0.428	0.000	-0.636	-0.221	4.358	0.030	0.423	8.292	0.024	0.879	-0.281	0.329	-0.313	0.021	-0.578	-0.048
Drought					0.092	0.661	-0.318	0.501	-32.020	0.000	-45.932	-18.108	-0.477	0.000	-0.667	-0.287	-0.230	0.027	-0.433	-0.026
Salinity					-0.614	0.022	-1.142	-0.087	16.357	0.583	-42.092	74.806	-1.089	0.000	-1.632	-0.545	-0.648	0.000	-0.941	-0.354
Share of Crop Lost Due to:																				
Submergence									-0.239	0.043	-0.472	-0.007					-2.158	0.818	-20.569	16.252
Drought									-0.244	0.052	-0.490	0.002					-53.691	0.000	-76.032	-31.349
Salinity									-0.607	0.002	-0.982	-0.231					-11.074	0.768	-84.747	62.598
Large Loss Dummy																	3.394	0.133	-1.036	7.824

Opinion on Stressors

Our results suggest no statistically significant relationship between a farmer's opinion on submergence as a problem and their degree of risk aversion; however, we find that there is a statistically significant relationship between a respondent's opinion on drought and salinity as problems and a person's degree of risk aversion. The magnitudes of these suggest that the mean person in the sample in terms of their opinion on salinity as a problem would have an estimated risk aversion parameter 9% smaller than individuals who strongly felt that salinity was not a problem but 28% larger than individuals who strongly agreed that salinity was a problem, and in the case of individual opinions on drought, that mean person in terms of their opinion on drought would have a risk aversion parameter 20% smaller than individuals who strongly felt that drought was not a problem and 21% larger than individuals who felt strongly that drought was a problem.

Stress Proneness and Interactions

By itself, we find no evidence to suggest that individuals who are in more stress-prone conditions have different degrees of risk aversion from others. Models 4 and 5 include interactions with stress proneness. In Model 4, we do not find evidence that either increasing submergence or increasing droughts interacted with their respective proneness measure yields a statistically significant change in risk aversion, implying that for individuals already in highly stress prone areas due to salinity will actually become more risk averse relative to those in less risk prone areas after experiencing worsening amounts of salinity. The economic importance of this change is relatively modest. For example, if a person reported experiencing three more periods of salinity in the second survey round (2016) over the first survey round (2013), they would see their σ fall by 0.012 or approximately 4% from the mean degree of risk aversion which represents about 1% decline in an agents certainty equivalent in a small bet. In addition, we do not find evidence to support the idea that stress proneness measures intensify or moderate changes in risk preferences due to crop losses as a share of total output. In summary, as to our first hypothesis (RH.1) related to the interaction between increased stress and stress proneness, we find limited evidence that the effects of increasing stress on an individual's risk preferences are either augmented or diminished by prior experience with such stressors. Model 5 suggests that there is no relationship between stress-proneness and most recent season losses and a person's degree of risk aversion; while Model 4, which interacts changing frequency with the stress proneness metrics, suggests that individuals in areas with greater degrees of salinity proneness and who state increasing incidences of salinity do in fact have modestly increasing degrees of risk aversion, but the economic importance is somewhat weak. Note, only our salinity index measure provides a direct measure of stress proneness at present; therefore, as we incorporate appropriate precipitation and temperature indices in subsequent iterations of this work, we will revisit this matter.

Change in Reported Frequency

Respondents could report having at most 5 more (or fewer) years of a salinity, submergence, and drought between the two survey periods. Models 2, 3, 4, and 5 all include these as regressors. Models 2 and 4 do not control for recent experiences of crop loss due to stressors and may, therefore, have some omitted variable bias. In these two models, changes in submergence experience do not have a statistically significant impact on risk aversion, but in Models 3 and 5, there is a modest, positive effect on the risk aversion parameter that is only statistically significant at the 10% level. The result for changes in drought is similarly non-robust to specification as well as small in magnitude. Changes in salinity, however, appear to have a strong and statistically significant effect on a farmer's degree of risk aversion, but we find that increasing experiences with salinity decreases risk aversion by increasing the risk aversion parameter by about 0.027 on average (about 10% from the baseline estimate). Consequently, for RH.2 and RH.3, we find, in fact, that risk aversion declines with increasing incidences of both submergence (for Models 3 and 5) and salinity (in Models 2, 3, 4, and 5), contrary to expectations. However, efforts to control for the nonlinear nature of the relationship did not yield meaningful results; therefore, we have not yet tested RH.3.

Share of Crops Lost Due to Stressor

Models 3 and 5 allow for tests of whether recent losses of crops due to a stressor affect behaviors. High degrees of correlation between the interaction terms and the share-loss in Model 5 could be confounding factors, so we suggest that there is modest evidence that increased losses due to submergence relate to higher degrees of risk aversion. Both Models 3 and 5 indicate a negative relationship, and the former model which excludes interactions while still controlling for stress proneness suggests that (at the 10% significance level) modest evidence that greater losses due to submergence will cause more risk aversion. Shares of crop lost due to drought, however, relate to increased preference for risk, and this finding is both statistically and economically significant across both models. A major loss, for example, amounts to 25% in the preceding year could yield an increase in the risk aversion parameter by greater than 100%. However, a more modest interpretation about the mean of the sample suggests that the average person who experiences the average crop loss due to drought would see their risk aversion parameter increase in magnitude by between 4% and 6% - perhaps relevant but small.

As to RH.4, our results suggest in Model 3 that increasing crop shares lost due to submergence may cause a large increase in risk aversion, but this finding only holds at the 10% significance level. On the other hand, we find that individuals who experienced losses due to drought in the previous season would become more risk preferring. So, we have modest evidence that crop losses due to stressors in a recent season yield changes in risk preferences but not strong evidence on the specific direction. Our current method of calculating counterfactual production levels by which we can infer the level of output losses implied is somewhat simple; therefore, subsequent work will consider a more sophisticated method of estimating such output levels.

Time Preference, Stress Proneness, Opinions on Stress, and Stress Experience

In this discussion, we omit most discussion of the opinions on stressors as they figure modestly, and the remainder of the discussion on time preferences mirrors that of the preceding section. However, before we begin this section, we should recall the construction of our discount function and note that the discounted value of a given payment can be stated as follows.

$$DV = \left(e^{-\delta t} * x^{\sigma} - \kappa\right)^{1/\sigma}$$

It is not enough to simply consider how a given factor effects the discount rate, but we must consider the simultaneous and statistically significant effects of all in order to arrive at a meaningful interpretation of the effect. For the sake of this conversation, we will discuss the statistical significance and signs of each variable, but we consider the economic impact in order to understand whether support exists for a given hypothesis. Specifically, we will let x = 1000 in place of 1000 Taka, and we can measure the impact of the DV for changes in given statistically significant variables. Note, because of the structure of the DV function, it is highly likely that nonlinearities exist in relationships. While not all variables are continuous, we note that the slope of the DV function relative to any variable z_i and assuming a one year time horizon can be stated as follows:

$$\frac{\partial DV}{\partial z_i} = \frac{-\,{}^{\partial\sigma}/_{\partial z_i}}{\sigma^2} * \left(e^{-\delta} * x^{\sigma} - \kappa\right)^{1/\sigma} * ln\left(e^{-\delta} * x^{\sigma} - \kappa\right)\left(e^{-\delta} * x^{\sigma}\left(\frac{\partial\sigma}{\partial z_i}\text{lnx} - \frac{\partial\delta}{\partial z_i}\right) - \frac{\partial\kappa}{\partial z_i}\right)$$

Stress Proneness and Interactions

Our stress proneness metrics generally have a negative sign across Models 1, 2, and 3 in the estimation of discount rates; however, only in Model 2 does the sign appear as statistically significant for the Salinity Index. The parameter in the discount rate function across the three models range from -0.103 to -0.274. In the estimation of the time bias, the effect of drought and flood proneness is generally not statistically significant, but the salinity index has a positive sign across Models 1, 2, and 3, and the coefficient is statistically significant in one regression. The parameter estimates across models 1, 2, and 3 range from 0.202 to 0.622. Note, the first result implies a reduction in the discount rate on the future and the latter implies that the agent would have a smaller time bonus, thus these effects on patience are offsetting and must be combined to provide a meaningful interpretation. For the sake of economic interpretation, starting from the baseline estimates of Model 2, the person at the mean salinity level (approximately 1), they would have a discounted value about 85% of that of the person in a non-saline area but 600% of the person in the highly saline level, suggesting in this case, a lower degree of patience among individuals in highly saline environments.

The proneness interaction terms merit modest consideration. In neither model 4 nor model 5 does the interaction between submergence proneness and either frequency or incidence of submergence appear statistically significant. However, drought proneness interacted with either a change in frequency or recent incidence of share loss lowers the discount rate, with the effect being statistically significant in Model 5. When connected with the parameter estimate for the influence of this latter interaction on κ, a farmer with 30% of his/her land in high land and experiencing a 5% crop loss would have a discounted value of 1000 taka in a year at a value of less than 25% larger than the mean farmer with 15.2% of land in high land and 0.8% crop loss. Note, both would already have discounted nearly 95% of that value in the first case, however due to the already very high discounts on the future. In terms of salinity interactions, the sign of the parameters are similar, but salinity has a statistically significant effect only in Model 4 on both δ and κ. The effect reduces the discount rate on the future with an offsetting increase in the time bias parameter. In economic terms, the effects are, in fact, somewhat modest. As a farmer goes from non-saline to highly saline and from reporting no change to significant changes in incidence, the discounted value increases slightly up to the point where a farmer reports two more incidences of salinity and lives in an area with a salinity index of 3 but then actual declines modestly thereafter such that the discounted value of the mean person and the person in an area of extreme salinity are essentially same.

In considering our hypotheses related to time preferences, recall that TH.1 suggests that individuals in more stress prone should have time preferences that are less responsive to changing incidences of the stressor. In considering our estimates from Model 4 and Model 5 as discussed above, we find that there is no evidence that being in a submergent prone condition interacted with either changing stress incidence or recent losses has an impact on an individual's level of discount of the future. On the other hand, we find evidence that individuals in more drought prone areas will tend to discount the future less on net while individuals in more salinity prone areas will discount the future more (but modestly so) than individuals who only have moderate levels of salinity and small increases in incidence.

Change in Frequency

Models 2 through 5 all include the change in frequency of the stressor as an independent variable. The impact of increasing submergence increases the discount rate across all regressions and has a statistically significant effect in Models 2 and 4 at the 95% confidence level and for Model 3 at the 90% confidence level. Increasing frequency of drought has a positive and statistically significant effect on the discount rate at the 95% confidence level in Models 3, 4, and 5, and a negative but not statistically significant effect in model 2. Similarly, increasing the frequency of reported salinity stress over the preceding years relative to the first survey round yielded a positive and statistically significant effect on discount rates in Models 2, 3, 4, and 5. Note, the results on the time bias parameter do not perfectly mirror the effects on discount rates. Specifically, the coefficient on increasing submergence frequency is negative and statistically significant in Models 2 and 4, positive and statistically significant in Model 3, and positive but no statistically significant in Model 3, suggesting some ambiguity of the influence on submergence in this model. However, the effect on drought is more consistent, with the impact being to further reduce the time bias parameter in Models 3, 4, and 5, and increase it in Model 2 but in a non-statistically significant manner. Similarly, increasing salinity reduces the time bias parameter in models 2, 4, and 5 in a statistically significant manner. In considering hypothesis TH.3, we contend that individuals reported changes in the frequency of a stressor acts as a metric of how a person might forecast future stress experiences. Recall, TH.3 suggested that perceptions of a worsening environment in the future could cause an increasing discount rate on the future. On net, we find across all stress types that increasing incidences of stress correspond with rising discount rates on the future; however, because of the nature of our estimation and findings related to the time bias estimate, the actual implications are that individuals become more nuanced; therefore, we will return to this component momentarily in our economic analysis of the findings as these provide a better sense of the nonlinearity of this factor. However, because of its nonlinearity, we can reject the notion the notion that changing incidence by itself causes an increasing discount on the future.

Share of Crops Lost Due to Stressor

For TH.2, we argued that losses (or wealth effects) associated with stressors would reduce patience. Models 3 and 5 consider this by accounting for changes output due to a stressor. Model 3 provides contradictory results. In the case of submergence, individuals appear to become more patient in response to greater crop losses; while individuals with greater crop losses due to drought become less patient. This latter effect also holds for Model 5. In neither instance does greater recent year loss associated with salinity yield a statistically significant effect on the individual discount rate

Economic Interpretation of Key Findings

Following is an economic interpretation of Models 1 and Model 5. Model 1 captures the specific role of opinions, and Model 5 nests multiple aspects of the roles of various stressor related factors in preferences. First, Table 9 presents a brief analysis of the role of opinions on salinity and drought on risk and time preferences. We calculate the certainty equivalence for each level of σ as well as calculate the discounted value of 1,000 Taka in one year for different values of σ, κ, and δ. The certainty equivalent is simply the certainty equivalent of a lottery which pays 10 Taka if the agent “loses” and 90 Taka if the agent “wins”.[3] In this case, while we observe that salinity and drought have a statistically significant effect on an agent’s risk preferences, we observe only modest differences in the measured certainty equivalent,

[3] This illustrative certainty equivalent is therefore calculated as follows: $CE = (0.5 * 10^{\sigma} + 0.5 * 90^{\sigma})^{1/\sigma}$

suggesting small differences in behavior. However, we note fairly large differences in discounted value of a payment in one year. While all agents discount the future very highly, those that agree or strongly agree that salinity is a significant crop stressor discount the values substantially further. Using the discounted values to infer an annualized discount rate, a person who strongly disagreed that salinity was a crop stressor had an annualized one-year discount rate of 249 percent while the person who strongly agreed that salinity was a major stressor had a discount rate of 399 percent.[4] The effect of agreement on the importance of drought is less strong; however, it suggests that those who agree or strongly agree that drought is an important crop stressor are measurably more patient, and we recall the relatively wide confidence intervals on these measurements.

Table 9. Economic Analysis of Estimated Values for Risk and Time Preferences

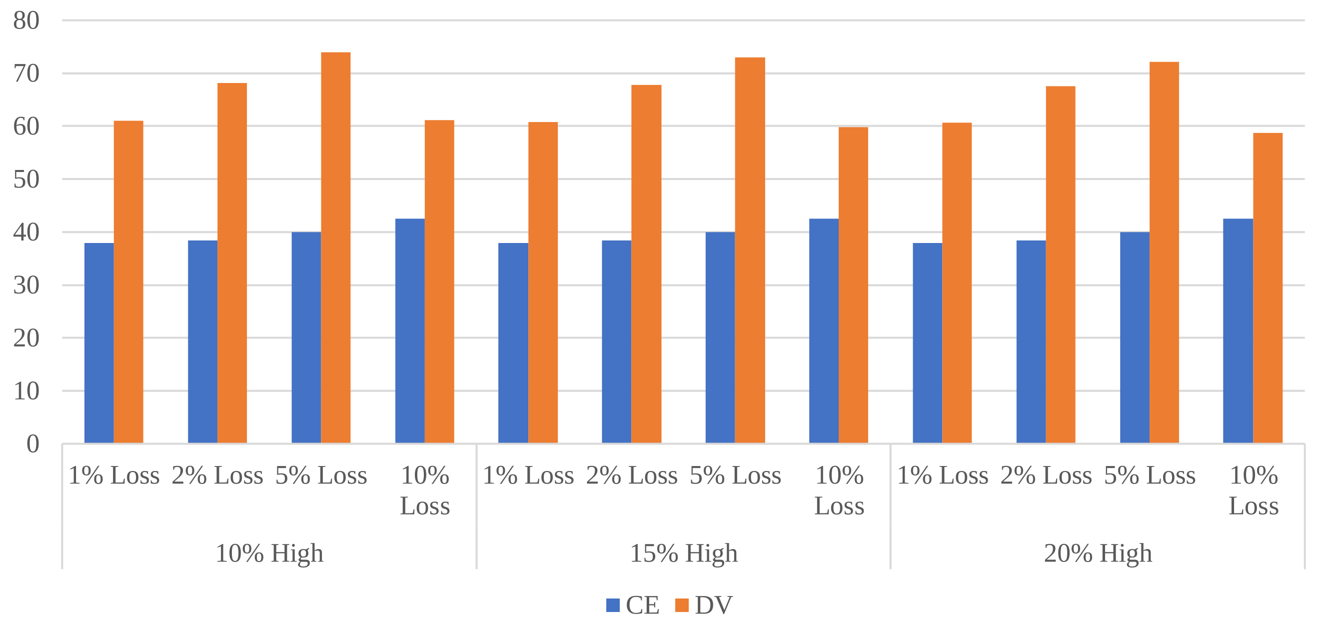
		σ	δ	κ	CE	DV
Opinion on salinity as a crop stressor	Strongly Disagree	0.34	2.31	-3.40	39.30	83.00
	Disagree	0.31	2.09	-2.75	38.60	76.29
	Neither	0.28	1.86	-2.09	37.91	62.32
	Agree	0.25	1.64	-1.44	37.22	41.31
	Strongly Agree	0.22	1.41	-0.78	36.54	18.41
Opinion on drought as a stressor	Strongly Disagree	0.35	2.03	-2.70	39.53	60.57
	Disagree	0.32	2.03	-2.65	39.00	65.87
	Neither	0.30	2.04	-2.61	38.47	73.48
	Agree	0.28	2.04	-2.56	37.95	84.53
	Strongly Agree	0.26	2.05	-2.52	37.43	100.95

Now, with Model 5 there a richer set of possible considerations. We first consider how both the share of crop lost due to drought and its interaction with the percent of land held in high ground affect time preferences and risk preferences. Note, both the interaction term and percentage lost are relevant in the calculations of the discount rate and time bias parameter; however, in calculating the risk preferences, we assume that the parameter on the interaction term took a value of zero given that it was not found to be statistically significant. Figure 2 below shows how the individuals certainty equivalent evolves across various degrees of loss. Note, the change in the certainty equivalent is invariant to the amount of land considered to be high or drought prone land, but it is modestly positive with respect to changes in the degree of loss. Since average losses across the sample due to drought are relatively low (about 1%), we

[4] This is calculated as the solution of $DV = 1000 * e^{\delta}$ such that what we call the effective one-year annualized discount rate is $\delta = -\ln(DV/1000)$.

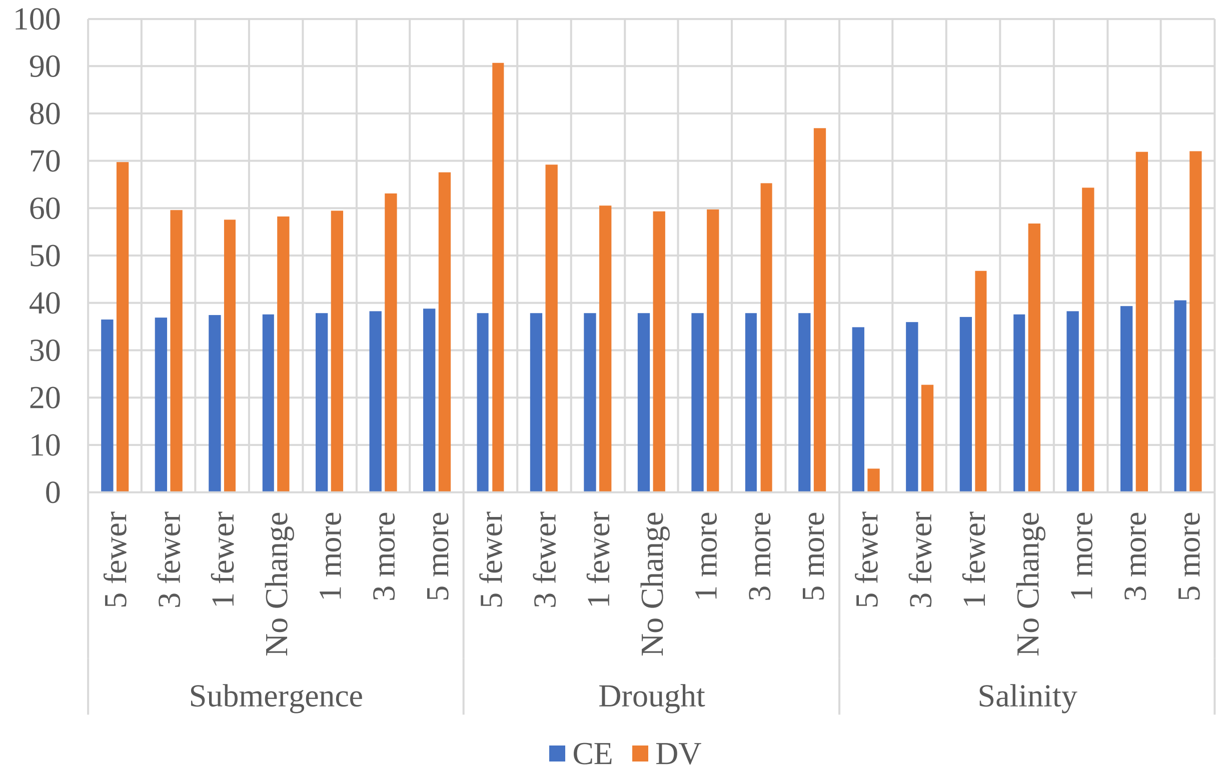
consider losses ranging from 1%, 2%, 5%, and 10%. The change in certainty equivalent implies decreasing risk aversion with greater losses. At the same time, we note while the interaction effect has a modest bearing on the discounted value measure across households based on the share of land held in high land, this effect is quite modest. However, across all land share scenarios, the degree of patience exhibited by an individual is growing as losses increase from 1% to 2% to 5%, but then falls as the losses reach 10%, suggesting something of a nonlinearity in patience suggested in other areas of the literature.

Figure 2. Certainty Equivalents and Discounted Values by Share of High Land and % Loss Due to Drought



Next, let us consider the interpretation of Model 5 results. Recall, the independent variable here is the change in reported years in which a person experienced stressor between the 2016 and 2013 surveys. Recall that the maximum value this could take would be 5. That is, the individual could report 0 stress events in the previous 5 years in the 2013 survey and could report 5 stress events in the previous 5 years in the 2016 survey. Because of overlap, we recognize the practical impossibility of a true change of five, but some agents made such a reports as noted in Figure 1 earlier. Similarly, a value of -5 would imply five fewer incidences, or the person reported the stressor in the previous 5 years in the 2013 survey but reported no stressors in the previous 5 years in the 2016 survey. Using the statistically significant parameter estimates, constant terms, and mean values of the data, we calculate the certainty equivalents and discounted values as before to show, in economic terms, the importance of these factors in the formation of preferences. Figure 3 below provides these results.

Figure 3. Certainty Equivalents and Discounted Values by Stressor Type and Change in Frequency Between Survey Rounds



For sake of space, we note that the relationship in changes reported and both the certainty equivalent and discounted value were somewhat similar for both reported changes in submergence and reported changes in drought. First, we observe that for both those experiencing greater incidences of submergence and drought that there is negligible decline in risk aversion, and for those experiencing increasing degrees of salinity stress that there measured risk aversion is declining modestly more quickly. However, in all cases, the effects are modest in nature. Again, the discounted value calculations reveal more interesting results. Specifically, the nonlinear relationship between reported stress experience and patience. Individuals reporting either greater increases or greater decreases in stress due to submergence or drought appear to demonstrate greater measured patience due to the higher calculated discount rates. When considering changing experiences with salinity, as individuals move from reporting substantially fewer instances of salinity damage to substantially more instances of salinity damage, they become much more patient as the discounted value moves from less than 10 Taka to just over 70 Taka.

Considering Hypotheses.

We find limited evidence that a farmer's degree of risk proneness interacted with either changing stress frequency or recent loss due to crop stress had an effect on risk aversion. In one model, we observed that increasing frequency of droughts and increasing drought proneness lead to modest but not economically meaningful increases in risk aversion. Contrary to expectations, we find that increasing incidence submergence, drought, or salinity corresponded with declining degrees of risk aversion. Recent crop losses due to a submergence increase risk aversion (at the 10% significance level thus modestly supporting our hypothesis), but recent crop losses due to drought yields has a statistically and economically significant effect, with a major loss in the previous year due to drought (25%) yielding an increase in the risk aversion parameter by 100%. In the context of time preferences, we find evidence that increasing drought proneness interacted with increased crop losses has a statistically significant effect on an individual time preference parameters and yields a non-linear relationship with crop losses and patience such that individuals become increasingly patient as loss increase up to a certain point but more significant losses will then cause patience to fall again. Finally, increasing incidences of stressors are statistically significant for submergence, drought, and salinity; however, the effect is highly nonlinear for submergence and drought such individuals experiencing either no change or one fewer incidence were the least patient. Those reporting substantially fewer cases of salinity demonstrated lower patience than those who reported more frequent incidences of salinity. At present, the findings remain preliminary and merit more consideration before drawing policy conclusions and implications; however, the findings provide further important evidence of the relevance of weather and climate related events in the economic preferences of farmers.

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Appendix 1. Comparing Index and Imputed Wealth Measures

In order to control for wealth, income, and changes in economic condition, various metrics were calculated. The primary sources of wealth, aside from rice stocks, are considered to be land, physical assets other than residence, and animal assets. The survey instrument did not include a specific question about home attributes, so we cannot directly consider this piece of information in this analysis. Two approaches were used in order to construct measures of wealth: (1) using available price/value data to construct values for land, physical assets, and animal assets based on some base year values and (2) pursuing the principal components index value construction proposed by Filmer and Pritchett (2001) and used in the following studies. There are merits to considering both approaches; therefore, both are discussed here.

Procedure 1. Value Imputation Using BIHS and RMS Data

In the first approach, data on livestock, asset, and land from the Bangladesh Integrated Household Survey for 2011 and 2015 (Ahmed, 2013 and Ahmed, 2016) were used in order to construct measures of livestock, asset, and land values as follows. Except in one case, base year prices or values for livestock, farm assets, and land were derived from 2011 survey.

Imputing Land Values

In order to construct measures of land values, the BIHS provides a nationally representative sample of households, and households were asked to report their various plots of land and to report the expected value of such land if it were sold. Households in the RMS data set also reported the size of their various plots; therefore, the values provided in the BIHS were used to provide a reasonable metric of land value, notwithstanding differences in land quality or type. Upon inspecting the BIHS data, a nonlinear relationship (logarithmic) between the plot value and plot size existed; therefore, in order to impute a measure of the value per plot size, the following regression was run with the 2011 data only. Note, ideally, one could control for land type, but as this question is asked in the BIHS but not in the RMS, that concordance could not occur here. The results of that regression are shown below.

Appendix Table 1.1 Regression of Plot Value as a Function of Size

	Coefficient	p-value	95% Confidence Interval	
LN(Plot Size in Acres)	211838	0.000	204155.4	219520.4
Constant	753164	0.000	735639.3	770687.7

$F(1, 25394) = 2921$ p-value = 0.000 Adj. R-squared = 0.103

Given these results, we originally imputed the value per acre of owned land for each farmer as follows where corresponds with farmer i, t corresponds with year t, and j corresponds with plot number.

$$Land\ Value_{it} = \sum_{j=1}^{N} 753{,}163.5 + 211{,}837.9 * \ln\left(plot_{acreage_{itj}}\right)$$

However, upon inspection of this imputation, it appeared to severely undervalue farms with large acreage and perhaps fewer plots while overvaluing some small farms with many plots. Consequently, as a reasonable, if imperfect measure, the same parameters were used, except that instead of using the natural log of each plot, we simply calculated the imputed land value with the natural log of total acreage owned. This result may tend to undervalue some very small farms, but it does not create the same level of anomalies.

Calculating Asset Values

In determining asset values, the list of farm assets which might possibly have some cash value was used as the measures of choice, and all that had a reasonable match in the BIHS data were so matched. First, average values were calculated for farm implements/assets in the BISH data. Values were obtained for the following: (1) plough and yoke sets, (2) manual sprayers, (3) wheel barrow, (4) bullock cart, (5) push cart, (6) tractor, (7) power tiller, (8) trolley/trailer, (9) thresher, (10) fodder cutting machine, (11) diesel motor pump, (12) other heavy machinery, (13) spraying machines (chemical/fertilizer). These were then matched to the data in the RMS data set. Note, because the RMS data only asks whether individuals had carts, carts were valued at the average value of the bullock cart and pushcart value in the BIHS. Similarly, the RMS survey only asks whether households have a sprayer and the BIHS contains information on both Manual Sprayers and Spraying Machines; therefore, and average value of these were taken as well. Below is a tabulation of the concordance and associated values.

Appendix Table 1.2 Concordance of RMS and BIHS Data for Asset Valuation

RMS Item	BIHS Study	2011 Reported Value
Carts	Bullock cart and Push Cart	2,524.59
Chaff Cutter	Fodder cutting machine	179.72
Diesel pumps	Diesel motor pump	7,625.93
Four wheelers/Two wheelers	Other heavy machinery	2,7296.76
Ploughsets	Plough & yoke for animals	198.77
PowerTiller	Power tiller	41,835.29
Sprayer	Manual Sprayer and Spraying machines (chem./fertilizer)	753.40
Thresher	Thresher	4,990.93
Tractors	Tractor	30,005.00
Trolley	Trolley/trailers	42,937.5
Wheelbarrows	Wheelbarrow	5,700

Calculating Animal Values

Similarly, in constructing values for livestock owned by RMS participants, average value data from the BIHS survey was calculated for the following animals: buffalo, bullocks, chicken, cows, ducks, goats, pigs, sheep, and heifers with calves. Note, chicken values in the BIHS differentiated broilers and laying hens; therefore, an average price was constructed, and the

BIHS only had valuation for milk cows, but given what is likely the similar valuation for heifers with calves, the milk cow average value was assigned to the heifers with calves reported in the RMS data. Also, as there was no value for pigs in the 2011 BIHS survey, the 2015 value was used (For obvious reasons, few individuals keep pigs as livestock). Below is the concordance constructed.

Appendix Table 1.3 Concordance of RMS and BIHS Data for Animal Valuation

RMS Item	BIHS Item	Value
Buffalo	Buffalo	25278.69
Bullocks	Bullock	13097.71
Chicken	Average Chicken Price	124.77
Cows	Milk cow	15356.38
Duck	Duck	194.51
Goats	Goat	2009.72
Heifers with calves	Milk cow	15356.38
Pigs	Pig	2576.19
Sheep	Sheep	1745.58

Calculating Wealth

From these calculations, we constructed two approaches to considering wealth for the household. One approach involves calculating wealth as the sum of the imputed value of a farmer’s land holding, their farm assets, and their stock of animals. The other approach calculates the farmers wealth variable as being only their farm assets and their stock of values. We can then consider the two forms of wealth separately in subsequent analyses.

Procedure 2. Constructing Wealth Indexes Using Principal Components Analysis

For the second procedure, we performed a principal components analysis as proposed by Filmer and Pritchett (2001) and further explained in Vyas and Kumaranayake (2006). Note, given the large number of possible assets, animals, and land itself, an appropriate method of dimension reduction is relevant while maintaining the explanatory information contained within those values. By way of a brief explanation, principal components analysis will create N linear combinations of the variables considered as part of a dimensional reduction technique. The process of creating each linear combination follows sequentially. The first principal component is the linear combination of explanatory values that explains the largest portion of the variation in the set of data, and the second explains the second largest portion, and so on until all variation is explained. Consequently, in that sense, it represents an index of a household’s wealth (or other attributes as the case may be) and can be used to consider the relative wealth of different households. As explained by Vyas and Kumaranayake (2006), the first principal component in a variety of studies has been explained to explain between 12% and 27% of the total variation in various N dimensional asset lists. In their study, they found that it captured between 11.1% and 16.0% of the variation across household data from different levels of household data (rural, urban) and two countries (Brazil and Ethiopia).

Step 1 in the process of constructing an index requires that we select a set of assets or other values with which to perform the principal components analysis. We took two approaches in the principal components analysis. One approach measured wealth as simply a function of assets and animals and the other approach included total acres owned as well. All variables included in this index construction appear in Table A below.

Appendix Table 1.4 Elements to Include in Wealth Indices

Land and Animals	Equipment and Household Assets
Owned Acreage (in one index)	Bicycle
Sheep	Carts
Buffalo	Chaff Cutter
Bullocks	Computers
Chicken	Coolers
Cows	DVD Players
Ducks	Diesel Pump
Goats	Duster
Heifer with calf/calves	Electric Fan
Pigs	Four Wheelers
	Mobile Phones
	Plough Sets
	Power Tiller
	Radio
	Refrigerators
	Sprayer
	Television
	Thresher
	Tractors
	Trolley
	Two Wheelers
	Wheel Barrows

Step 2 in the process of constructing the index required the actual implementation of the principal component analysis. In addition, in order to make the wealth indexes comparable across the two waves of the panel, we performed the analysis over the pooled set of data, thereby allowing for the construction of an index across households in a given period of time as well as comparisons of a households index over time. After performing the analysis we obtain the eigenvalues of the principal components and explanatory values of each. These are shown in Table C below. The first principal component in either construction of the index explains about 11% of the variation in the data contributing to the index. While relatively low, this result is consistent with what has been seen in the literature.

Appendix Table 1.5 Principal Component Eigenvalues and Explanatory Proportion

	Excluding Acreage		Including Acreage	
Component	Eigenvalue	Proportion	Eigenvalue	Proportion
Component 1	3.30381	0.1101	3.33918	0.1077
Component 2	2.18726	0.0729	2.19563	0.0708
Component 3	1.3666	0.0456	1.37183	0.0443
Component 4	1.28128	0.0427	1.28174	0.0413
Component 5	1.23372	0.0411	1.24133	0.04
Component 6	1.1203	0.0373	1.14671	0.037
Component 7	1.09306	0.0364	1.09334	0.0353
Component 8	1.04817	0.0349	1.04819	0.0338
Component 9	1.02957	0.0343	1.03247	0.0333
Component 10	1.0142	0.0338	1.02135	0.0329
Component 11	1.00321	0.0334	1.00365	0.0324
Component 12	1.00148	0.0334	1.00306	0.0324
Component 13	0.972579	0.0324	0.997892	0.0322
Component 14	0.94546	0.0315	0.945462	0.0305
Component 15	0.93291	0.0311	0.934732	0.0302
Component 16	0.905882	0.0302	0.908824	0.0293
Component 17	0.869145	0.029	0.899402	0.029
Component 18	0.854073	0.0285	0.869088	0.028
Component 19	0.84502	0.0282	0.845218	0.0273
Component 20	0.765115	0.0255	0.83399	0.0269
Component 21	0.753894	0.0251	0.765091	0.0247
Component 22	0.720809	0.024	0.752283	0.0243
Component 23	0.697037	0.0232	0.719924	0.0232
Component 24	0.683281	0.0228	0.697027	0.0225
Component 25	0.641676	0.0214	0.683234	0.022
Component 26	0.615196	0.0205	0.641675	0.0207
Component 27	0.59472	0.0198	0.615079	0.0198
Component 28	0.570117	0.019	0.59419	0.0192
Component 29	0.552805	0.0184	0.569583	0.0184
Component 30	0.397609	0.0133	0.551715	0.0178
Component 31	NA		0.397113	0.0128

In **Step 3**, we construct the actual index. This requires the use of the factor scores (or eigenvector) of the first principal component. The index for each household is therefore constructed as follows:

$$Index_{it} = \sum_{j=1}^{N} \gamma_j \left(\frac{x_{ijt} - \bar{x}}{\sigma_j} \right)$$

In the above function, i corresponds with the individual, t corresponds with the period, and j corresponds with the asset. In this context, γ_j is therefore the factor score of asset j, x_{ijt} is the amount of asset j held by individual i in period t, $\bar{x}$ corresponds with the average value of asset j (over all time periods in this case), and σ_j corresponds with the standard deviation of asset j around its mean. Table D. provides the factor scores (a.k.a., the eigenvector of the first principal component) of the first principal component which would is used in constructing the wealth index. Positive values are associated with higher wealth, and negative values are associated with a lower wealth index. Essentially, the factor score divided by an asset's standard deviation become the weight on a given household's specific asset deviation from the mean. All of these weights and factors are shown in Table D as well.

Appendix Table 1.6 Factor Scores

	Cross-Year Mean and Standard Deviation		Assets and Animals Only Principal Components Analysis		Assets, Animals, and Land Principal Components Analysis	
Variable	$\bar{x}$	σ	Factor Score	Factor Score/ σ	Factor Score	Factor Score/ σ
Own Acreage		5.21			0.12	0.02
Sheep	0.04	0.41	0.04	0.09	0.04	0.09
Baffalo	0.05	0.67	0.04	0.07	0.05	0.07
Bullocks	0.18	0.65	0.18	0.28	0.18	0.28
Chicken	11.80	92.90	0.08	0.00	0.07	0.00
Cows	1.47	1.63	0.12	0.07	0.12	0.08
Ducks	4.20	7.22	0.02	0.00	0.02	0.00
Goats	0.99	1.88	0.17	0.09	0.17	0.09
Heifer & Calves	0.37	0.82	0.21	0.25	0.21	0.25
Pigs	0.04	1.00	-0.01	-0.01	-0.01	-0.01
Bicycle	0.49	0.66	0.27	0.41	0.27	0.41
Carts	0.01	0.13	-0.01	-0.08	-0.01	-0.05
Chaff Cutter	0.04	0.27	0.03	0.13	0.03	0.13
Computers	0.03	0.18	0.16	0.89	0.16	0.87
DVD players	0.02	0.15	0.02	0.16	0.02	0.15
Diesel pumps	0.27	0.54	0.32	0.60	0.32	0.60
Duster	0.09	0.47	0.12	0.26	0.12	0.27
Electric Fan	1.83	1.81	0.32	0.18	0.32	0.18
Fourwheelers	0.00	0.07	0.06	0.93	0.06	0.91
Mobile phones	1.86	1.47	0.31	0.21	0.31	0.21
Plough sets	0.17	0.44	0.11	0.25	0.11	0.26
Power tiller	0.08	0.28	0.24	0.85	0.24	0.85
Radio	0.05	0.21	-0.02	-0.10	-0.02	-0.10
Refrigerators	0.16	0.39	0.21	0.54	0.21	0.53
Sprayer	0.42	0.59	0.32	0.54	0.32	0.54
TV	0.48	0.57	0.30	0.53	0.30	0.52
Thrasher	0.13	0.37	0.22	0.59	0.22	0.59
Tractors	0.01	0.09	0.03	0.30	0.03	0.30
Trolley	0.01	0.11	0.13	1.17	0.13	1.16
Twowheelers	0.08	0.31	0.26	0.87	0.26	0.86
Wheelbarrows	0.00	0.06	0.04	0.62	0.04	0.62

Comparison and Validation

For the sake of comparison, we show the correlation coefficient among all indices constructed as well as imputed values. In general, we find that the index value for a given year has correlation coefficient with the corresponding imputed value or wealth as being between 0.48 and 0.51, suggesting reasonable approximations. For example, the index for 2014 that does not include land in its construction correlates with value of assets and animals for 2014 at 0.4805. In addition, we find almost not difference between the indexes of a given year. That is the Index that excludes land has a correlation coefficient with the index that includes land of between 0.9944 and 0.9996, suggesting little practical difference, and it could allow us to include the no land indexes along with the simple acreage owned variable in subsequent work without worrying about excessive correlation.

Appendix Table 1.7 Relationship Between Wealth Index and Imputed Values

		2014		2017		2014		2017	
		Index No Land	Value (Assets + Animals)	Index No Land	Value (Assets + Animals)	Index With Land	Value (Assets + Animals + Land)	Index With Land	Value (Assets + Animals + Land)
2014	Index No Land	1							
	Value (Assets + Animals)	0.4805	1						
2017	Index No Land	0.6823	0.326	1					
	Value (Assets + Animals)	0.2795	0.498	0.4182	1				
2014	Index With Land	0.9944	0.4916	0.687	0.288	1			
	Value (Assets + Animals + Land)	0.4486	0.4408	0.4077	0.2786	0.486	1		
2017	Index With Land	0.6851	0.3319	0.9996	0.4226	0.6901	0.4156	1	
	Value (Assets + Animals + Land)	0.4202	0.35	0.4992	0.3851	0.4336	0.6083	0.5123	1

Appendix 1. References

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Appendix 2. Preliminary Calculation of Expected Output By Season

Farmers report their losses as a share of a seasonal output, but we do have a proper metric of the counterfactual (i.e., what would have their output been); therefore, we developed a simple method to calculate expected output so that we could better understand the severity of losses. For example, if one farmer had 100% loss in the Aus season but produces rice in both Aman and Boro with no effect, and another farmer has 100% loss in Aman season but only produces in that season, then the pain experienced is not the same. We performed the following simple approach to infer the severity of losses. Step 1. We calculate the average output per acre in each upazilla/thana for each season for the whole panel, so that we can suggest that the expected output per acre a farmer might produce would be equal to that average multiplied by the acreages cultivated. Step 2. We calculate the loss based on what the farmer indicates as the percentage lost. For example, if the expected output per acre is 1.5 tons, and the farmer cultivates one half of an acre but reports a 50% crop loss in the Aman season, then their imputed loss would be 0.1875 tons for the season when they report the loss. Step 3. We calculated losses as a share of total output (substituting expected output in the total for seasons when losses occur. For example, if the farmer actually produces in both Aman and Boro, then we could calculate the loss as a share of their total annual output (0.1875 tones/(1.5 tons + actual Boro output)).

Appendix 3. Complete Estimation Results

The following pages of the appendix include the complete estimations associated with the five models estimated.

Appendix Table 3.1a Risk Preference Estimates - Base Models												
	Model 1				Model 2				Model 3			
	Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval	
Constant	0.431	0.000	0.284	0.577	0.264	0.001	0.105	0.423	0.298	0.000	0.190	0.407
Household and Farm Characteristics												
Sex	-0.006	0.902	-0.098	0.087	0.048	0.605	-0.134	0.230	-0.011	0.916	-0.221	0.199
Age	-0.002	0.014	-0.003	0.000	0.002	0.075	0.000	0.004	0.002	0.070	0.000	0.004
Education	-0.001	0.609	-0.005	0.003	0.002	0.542	-0.004	0.008	0.001	0.852	-0.008	0.010
Hindu	-0.028	0.135	-0.065	0.009	0.015	0.678	-0.056	0.086	0.016	0.502	-0.030	0.061
Family Size	0.004	0.055	0.000	0.007	0.003	0.474	-0.005	0.010	0.001	0.740	-0.007	0.010
Household Head Leadership	0.029	0.002	0.011	0.048	-0.011	0.577	-0.051	0.028	-0.013	0.200	-0.032	0.007
Distance from Output Market	-0.002	0.801	-0.019	0.015	-0.015	0.001	-0.024	-0.006	-0.010	0.625	-0.049	0.030
Irrigation	0.074	0.047	0.001	0.146	-0.059	0.241	-0.157	0.039	-0.171	0.000	-0.240	-0.102
Δ in Non-Land Wealth (in Taka)	-0.000003	0.572	-0.000012	0.000006	0.000006	0.001	0.000003	0.000010	0.000005	0.004	0.000002	0.000009
Total Wealth (Taka)	0.000000	0.381	0.000000	0.000000	0.000000	0.383	0.000000	0.000000	0.000000	0.839	0.000000	0.000000
Stressors Metrics												
Proneness Measures												
Salinity Index	-0.008	0.161	-0.020	0.003	-0.022	0.067	-0.046	0.002	-0.004	0.895	-0.065	0.057
% High Ground	-0.012	0.743	-0.082	0.058	0.071	0.167	-0.030	0.171	-0.005	0.933	-0.111	0.102
% Low Ground	0.009	0.572	-0.023	0.042	-0.009	0.821	-0.087	0.069	-0.005	0.864	-0.066	0.055
Opinion on Stressor as Problem												
Submergence	0.008	0.258	-0.006	0.021								
Drought	-0.029	0.044	-0.057	-0.001								
Salinity	-0.022	0.012	-0.039	-0.005								
Change in Reported Frequency (2013-2016)												
Submergence					-0.006	0.496	-0.023	0.011	0.009	0.062	0.000	0.018
Drought					0.007	0.076	-0.001	0.015	-0.001	0.770	-0.010	0.008
Salinity					0.025	0.022	0.004	0.047	0.022	0.008	0.006	0.039
Share of Crop Lost Due to:												
Submergence									-0.168	0.071	-0.350	0.014
Drought									1.379	0.000	0.827	1.930
Salinity									-0.263	0.855	-3.085	2.560

Appendix Table 3.1b Discount Rate Estimates - Base Models												
	Model 1				Model 2				Model 3			
	Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval	
Constant	2.682	0.001	1.120	4.243	1.810	0.048	0.019	3.602	2.304	0.000	1.076	3.531
Household and Farm Characteristics												
Sex	-0.361	0.531	-1.488	0.767	0.604	0.592	-1.607	2.816	-0.031	0.980	-2.498	2.436
Age	-0.019	0.052	-0.038	0.000	0.015	0.247	-0.010	0.040	0.017	0.192	-0.009	0.044
Education	-0.028	0.227	-0.074	0.018	0.005	0.903	-0.069	0.078	0.001	0.982	-0.112	0.115
Hindu	-0.130	0.594	-0.608	0.348	0.271	0.486	-0.492	1.034	0.263	0.417	-0.372	0.897
Family Size	0.000	0.998	-0.062	0.062	0.036	0.366	-0.042	0.114	0.037	0.545	-0.083	0.157
Household Head Leadership	0.140	0.256	-0.101	0.381	-0.041	0.865	-0.507	0.426	-0.033	0.814	-0.306	0.240
Distance from Output Market	-0.065	0.394	-0.213	0.084	-0.167	0.001	-0.266	-0.069	-0.128	0.560	-0.559	0.303
Irrigation	0.485	0.224	-0.297	1.267	-0.743	0.263	-2.044	0.559	-2.138	0.000	-2.947	-1.329
Δ in Non-Land Wealth (in Taka)	0.0000	0.960	0.000	0.000	0.0001	0.026	0.000	0.000	0.0001	0.022	0.000	0.000
Total Wealth (Taka)	0.0000	0.060	0.000	0.000	0.0000	0.974	0.000	0.000	0.0000	0.964	0.000	0.000
Stressors Metrics												
Proneness Measures												
Salinity Index	-0.112	0.229	-0.295	0.070	-0.274	0.024	-0.513	-0.035	-0.103	0.756	-0.753	0.547
% High Ground	-0.024	0.955	-0.843	0.795	0.524	0.405	-0.711	1.760	-0.328	0.632	-1.667	1.012
% Low Ground	-0.105	0.615	-0.512	0.303	-0.254	0.620	-1.257	0.750	-0.263	0.536	-1.095	0.570
Opinion on Stressor as Problem												
Submergence	0.108	0.152	-0.040	0.255								
Drought	-0.225	0.089	-0.483	0.034								
Salinity	0.005	0.966	-0.215	0.224								
Change in Reported Frequency (2013-2016)												
Submergence					0.220	0.000	0.132	0.307	0.109	0.057	-0.003	0.220
Drought					-0.038	0.688	-0.224	0.148	0.115	0.050	0.000	0.230
Salinity					0.268	0.024	0.036	0.499	0.254	0.003	0.084	0.425
Share of Crop Lost Due to:												
Submergence									-2.150	0.031	-4.106	-0.195
Drought									12.665	0.000	6.637	18.693
Salinity									-5.620	0.670	-31.491	20.252

Appendix Table 3.1c Time Bias Estimates - Base Models												
	Model 1				**Model 2**				**Model 3**			
	Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval	
Constant	-5.101	0.032	-9.759	-0.444	-2.079	0.333	-6.285	2.127	-3.428	0.034	-6.598	-0.258
Household and Farm Characteristics												
Sex	0.280	0.840	-2.434	2.995	-1.331	0.628	-6.714	4.052	0.241	0.930	-5.144	5.626
Age	0.058	0.008	0.015	0.101	-0.033	0.293	-0.094	0.028	-0.035	0.239	-0.094	0.023
Education	0.025	0.652	-0.083	0.133	-0.039	0.662	-0.213	0.136	-0.025	0.839	-0.269	0.219
Hindu	0.251	0.665	-0.885	1.386	-0.702	0.446	-2.511	1.106	-0.748	0.249	-2.020	0.524
Family Size	-0.089	0.181	-0.220	0.042	-0.118	0.230	-0.311	0.075	-0.103	0.424	-0.357	0.150
Household Head Leadership	-0.759	0.038	-1.476	-0.042	0.022	0.965	-0.979	1.023	0.011	0.970	-0.577	0.600
Distance from Output Market	0.110	0.595	-0.294	0.514	0.346	0.001	0.141	0.551	0.257	0.575	-0.641	1.156
Irrigation	-1.361	0.165	-3.281	0.559	1.739	0.240	-1.161	4.639	4.776	0.000	2.729	6.823
Δ in Non-Land Wealth (in Taka)	0.000	0.882	0.000	0.000	-0.0003	0.040	-0.001	0.000	-0.0003	0.018	-0.001	0.000
Total Wealth (Taka)	0.000	0.363	0.000	0.000	0.0000	0.563	0.000	0.000	0.0000	0.814	0.000	0.000
Stressor Metrics												
Proneness Measures												
Salinity Index	0.202	0.262	-0.150	0.553	0.622	0.015	0.121	1.123	0.227	0.781	-1.372	1.827
% High Ground	0.525	0.584	-1.356	2.405	-1.382	0.368	-4.390	1.627	0.821	0.574	-2.045	3.687
% Low Ground	-0.146	0.761	-1.085	0.794	0.386	0.716	-1.695	2.466	0.413	0.647	-1.354	2.180
Opinion on Stressor as Problem												
Submergence	-0.178	0.376	-0.570	0.215								
Drought	0.655	0.025	0.084	1.227								
Salinity	0.044	0.851	-0.417	0.505								
Change in Reported Frequency (2013-2016)												
Submergence					-0.428	0.000	-0.636	-0.221	4.358	0.030	0.423	8.292
Drought					0.092	0.661	-0.318	0.501	-32.020	0.000	-45.932	-18.108
Salinity					-0.614	0.022	-1.142	-0.087	16.357	0.583	-42.092	74.806
Share of Crop Lost Due to:												
Submergence									-0.239	0.043	-0.472	-0.007
Drought									-0.244	0.052	-0.490	0.002
Salinity									-0.607	0.002	-0.982	-0.231

Table 3.2a Risk Preference Estimates – Expanded Models								
	Model 4				Model 5			
	Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval	
Constant	0.274	0	0.155	0.394	0.264	0	0.156	0.371
Household and Farm Characteristics								
Sex	0.083	0.235	-0.054	0.221	-0.029	0.388	-0.093	0.036
Age	0.002	0.023	0.000	0.003	0.002	0.001	0.001	0.004
Education	-0.001	0.705	-0.006	0.004	0.003	0.259	-0.002	0.008
Hindu	0.027	0.252	-0.019	0.072	0.001	0.977	-0.052	0.054
Family Size	0.001	0.794	-0.005	0.006	0.001	0.624	-0.004	0.006
Household Head Leadership	-0.012	0.432	-0.043	0.018	-0.013	0.150	-0.030	0.005
Distance from Output Market	-0.013	0.007	-0.023	-0.004	-0.010	0.071	-0.021	0.001
Irrigation	-0.056	0.009	-0.097	-0.014	-0.172	0.000	-0.243	-0.101
Change in Non_Land Wealth (in Taka)	0.00001	0.004	0.00000	0.00001	0.00000	0.004	0.00000	0.00001
Total Wealth (Taka)	0.00000	0.988	0.00000	0.00000	0.00000	0.598	0.00000	0.00000
Stressor Metrics								
Frequency Interaction								
Salinity Index*ΔSalinity	-0.009	0.495	-0.035	0.017				
% High Ground*ΔDrought	-0.001	0.944	-0.020	0.019				
% Low Ground*ΔSubmergence	-0.008	0.000	-0.012	-0.004				
Share Interaction								
Salinity Index*Salinity_Loss_Share					0.022	0.936	-0.512	0.556
% High Ground*Drought_Loss_Share					-1.081	0.124	-2.460	0.298
% Low Ground*Submergence_Loss_Share					-0.035	0.931	-0.830	0.760
Change in Reported Frequency (2013-2016)								
Submergence	-0.005	0.423	-0.016	0.007	0.009	0.061	0.000	0.019
Drought	0.007	0.032	0.001	0.014	-0.002	0.601	-0.009	0.005
Salinity	0.038	0.000	0.027	0.049	0.024	0.000	0.013	0.035
Share of Crop Lost Due to:								
Submergence					-0.020	0.954	-0.693	0.653
Drought					2.129	0.000	1.468	2.791
Salinity					0.184	0.898	-2.629	2.998
Large Loss Dummy					-0.091	0.261	-0.250	0.068

Table 3.2b Discount Rate Estimates – Expanded Models								
	Model 4				Model 5			
	Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval	
Constant	1.830	0.005	0.562	3.099	1.478	0.022	0.212	2.744
Household and Farm Characteristics								
Sex	0.908	0.283	-0.750	2.566	-0.299	0.372	-0.954	0.357
Age	0.013	0.114	-0.003	0.030	0.024	0.014	0.005	0.044
Education	-0.019	0.606	-0.089	0.052	0.029	0.350	-0.032	0.091
Hindu	0.383	0.180	-0.176	0.942	0.034	0.921	-0.630	0.698
Family Size	0.008	0.840	-0.071	0.088	0.029	0.341	-0.031	0.089
Household Head Leadership	0.038	0.866	-0.406	0.482	-0.025	0.837	-0.259	0.210
Distance from Output Market	-0.172	0.001	-0.272	-0.072	-0.130	0.055	-0.263	0.003
Irrigation	-0.695	0.007	-1.205	-0.186	-2.094	0.000	-2.907	-1.280
Change in Non_Land Wealth (in Taka)	0.000045	0.056	-0.000001	0.000090	0.000076	0.043	0.000002	0.000150
Total Wealth (Taka)	0.000000	0.619	-0.000001	0.000001	0.000000	0.935	-0.000001	0.000001
Stressor Metrics								
Frequency Interaction								
Salinity Index*ΔSalinity	-0.226	0.188	-0.562	0.110				
% High Ground*ΔDrought	-0.264	0.072	-0.552	0.024				
% Low Ground*ΔSubmergence	-0.102	0.002	-0.165	-0.038				
Share Interaction								
Salinity Index*Salinity_Loss_Share					-0.678	0.850	-7.704	6.349
% High Ground*Drought_Loss_Share					-15.409	0.037	-29.887	-0.930
% Low Ground*Submergence_Loss_Share					-3.016	0.463	-11.078	5.046
Change in Reported Frequency (2013-2016)								
Submergence	0.056	0.470	-0.095	0.207	0.145	0.016	0.027	0.264
Drought	0.255	0.000	0.173	0.338	0.102	0.025	0.012	0.191
Salinity	0.409	0.000	0.251	0.567	0.273	0.000	0.152	0.393
Share of Crop Lost Due to:								
Submergence					1.260	0.775	-7.361	9.880
Drought					20.866	0.000	13.263	28.470
Salinity					6.348	0.690	-24.852	37.549
Large Loss Dummy					-1.613	0.106	-3.567	0.340

Table 3.2c Time Bias Estimates – Expanded Models								
	Model 4				**Model 5**			
	Coef.	P > z	95% Conf. Interval		Coef.	P > z	95% Conf. Interval	
Constant	-2.186	0.159	-5.230	0.858	-1.721	0.280	-4.846	1.404
Household and Farm Characteristics								
Sex	-2.471	0.273	-6.884	1.942	0.726	0.379	-0.891	2.343
Age	-0.028	0.189	-0.071	0.014	-0.050	0.028	-0.094	-0.005
Education	0.024	0.761	-0.133	0.182	-0.087	0.215	-0.225	0.051
Hindu	-0.980	0.124	-2.229	0.269	-0.264	0.726	-1.741	1.212
Family Size	-0.061	0.464	-0.226	0.103	-0.091	0.181	-0.224	0.042
Household Head Leadership	-0.053	0.903	-0.907	0.801	0.015	0.954	-0.475	0.505
Distance from Output Market	0.332	0.001	0.131	0.534	0.259	0.060	-0.010	0.528
Irrigation	1.595	0.010	0.376	2.815	4.659	0.000	2.545	6.772
Change in Non_Land Wealth (in Taka)	-0.00025	0.016	-0.00045	-0.00005	-0.00026	0.010	-0.00045	-0.00006
Total Wealth (Taka)	0.00000	0.963	0.00000	0.00000	0.00000	0.590	0.00000	0.00000
Stressor Metrics								
Frequency Interaction								
Salinity Index*ΔSalinity	0.292	0.407	-0.397	0.981				
% High Ground*ΔDrought	0.364	0.257	-0.265	0.993				
% Low Ground*ΔSubmergence	0.273	0.004	0.085	0.460				
Share Interaction								
Salinity Index*Salinity_Loss_Share					0.549	0.942	-14.257	15.355
% High Ground*Drought_Loss_Share					36.888	0.092	-6.014	79.791
% Low Ground*Submergence_Loss_Share					9.086	0.385	-11.393	29.566
Change in Reported Frequency (2013-2016)								
Submergence	0.024	0.879	-0.281	0.329	-0.313	0.021	-0.578	-0.048
Drought	-0.477	0.000	-0.667	-0.287	-0.230	0.027	-0.433	-0.026
Salinity	-1.089	0.000	-1.632	-0.545	-0.648	0.000	-0.941	-0.354
Share of Crop Lost Due to:								
Submergence					-2.158	0.818	-20.569	16.252
Drought					-53.691	0.000	-76.032	-31.349
Salinity					-11.074	0.768	-84.747	62.598
Large Loss Dummy					3.394	0.133	-1.036	7.824

Appendix 4. Complete Results for Economic Implications of Statistically Significant Findings for Model 5.

Appendix Table 4.1 Estimated Risk and Time Preferences, Certainty Equivalents, and Discounted Values

		σ	δ	κ	CE	DV
	1% Loss	0.278	1.165	-1.006	37.915	60.964
	2% Loss	0.300	1.358	-1.506	38.425	68.150
	5% Loss	0.364	1.938	-3.006	39.970	73.919
10% High	10% Loss	0.470	2.904	-5.506	42.576	61.165
	1% Loss	0.278	1.157	-0.987	37.915	60.830
	2% Loss	0.300	1.343	-1.469	38.425	67.815
	5% Loss	0.364	1.899	-2.914	39.970	72.966
15% High	10% Loss	0.470	2.827	-5.322	42.576	59.826
	1% Loss	0.278	1.150	-0.969	37.915	60.704
	2% Loss	0.300	1.327	-1.432	38.425	67.512
	5% Loss	0.364	1.861	-2.821	39.970	72.135
20% High	10% Loss	0.470	2.750	-5.137	42.576	58.669
Submergence	5 fewer	0.219	0.266	0.945	36.506	69.729
	3 fewer	0.238	0.557	0.320	36.951	59.670
	1 fewer	0.257	0.847	-0.306	37.399	57.670
	No Change	0.266	0.992	-0.619	37.624	58.263
	1 more	0.276	1.138	-0.932	37.850	59.512
	3 more	0.295	1.428	-1.558	38.303	63.201
	5 more	0.314	1.719	-2.184	38.758	67.567
Drought	5 fewer	0.275	0.556	0.380	37.834	90.738
	3 fewer	0.275	0.759	-0.079	37.834	69.294
	1 fewer	0.275	0.963	-0.538	37.834	60.542
	No Change	0.275	1.064	-0.768	37.834	59.312
	1 more	0.275	1.166	-0.998	37.834	59.769
	3 more	0.275	1.370	-1.457	37.834	65.278
	5 more	0.275	1.573	-1.916	37.834	76.963
Salinity	5 fewer	0.147	-0.318	2.525	34.839	4.989
	3 fewer	0.195	0.227	1.230	35.951	22.720
	1 fewer	0.244	0.772	-0.065	37.085	46.748
	No Change	0.268	1.045	-0.713	37.658	56.824
	1 more	0.292	1.317	-1.361	38.236	64.399
	3 more	0.340	1.862	-2.656	39.402	72.008
	5 more	0.389	2.407	-3.951	40.579	72.036